
KGYM: A Platform and Dataset to Benchmark Large Language Models on Linux Kernel Crash Resolution

Alex Mathai^{1*}, Chenxi Huang^{2*}, Petros Maniatis³

Aleksandr Nogikh⁴, Franjo Ivančić⁴, Junfeng Yang¹ and Baishakhi Ray¹

¹Columbia University, ²University of Minnesota, ³Google Deepmind, ⁴Google
{alexmathai, junfeng, rayb}@cs.columbia.edu
{maniatis, nogikh, ivancic}@google.com
{huan2677}@umn.edu

Abstract

Large Language Models (LLMs) are consistently improving at increasingly realistic software engineering (SE) tasks. In real-world software stacks, significant SE effort is spent developing foundational system software like the Linux kernel. Unlike application-level software, a systems codebase like Linux is multilingual (low-level C/Assembly/Bash/Rust); gigantic (>20 million lines); critical (impacting billions of devices worldwide), and highly concurrent (involving complex multi-threading). To evaluate if machine learning (ML) models are useful while developing such large-scale systems-level software, we introduce KGYM (a platform) and KBENCHSYZ (a dataset). The KGYM² platform provides a SE environment for large-scale experiments on the Linux kernel, including compiling and running kernels in parallel across several virtual machines, detecting operations and crashes, inspecting logs, and querying and patching the code base. We use KGYM to facilitate evaluation on KBENCHSYZ, a crash resolution benchmark drawn from real-world Linux kernel bugs. An example bug in KBENCHSYZ contains crashing stack traces, a bug-reproducer file, a developer-written fix, and other associated data. To understand current performance, we conduct baseline experiments by prompting LLMs to resolve Linux kernel crashes. Our initial evaluations reveal that the best performing LLM achieves 0.72% and 5.38% in the unassisted and assisted (i.e., buggy files disclosed to the model) settings, respectively. These results highlight the need for further research to enhance model performance in SE tasks. Improving performance on KBENCHSYZ requires models to master new learning skills, including understanding the cause of crashes and repairing faults, writing memory-safe and hardware-aware code, and understanding concurrency. As a result, this work opens up multiple avenues of research at the intersection of machine learning and systems software.

1 Introduction

In recent years, there has been significant progress in using code LLMs (like CodeWhisperer [Amazon, 2023] and CoPilot [GitHub, 2021]) in all stages of the software cycle, including development, debugging, and testing. Despite being trained on large and complex open-source projects, LLMs are

*Denotes equal contribution

²<https://github.com/Alex-Mathai-98/kGym-Kernel-Playground>

often benchmarked on test sets like EvalPlus [Liu et al., 2023a], HumanEval [Chen et al., 2021], and APPS [Hendrycks et al., 2021] which are about³ to get saturated [Ott et al., 2022]. While useful, these benchmarks represent “green-field” SE by isolating coding to the task of solving programming puzzles. Unfortunately, such puzzles do not reflect the intricacies involved in everyday reasoning and solving of complex bugs in production-ready software.

Hence, newly introduced benchmarks (like SWE-Bench [Jimenez et al., 2024]) try to bridge the gap between existing tasks and realistic SE in “brown-field” environments, where LLM assistants edit, debug, and test production-ready software. Such benchmarks capture a more realistic SE setting: given a software repository, a natural-language (NL) description of a problem or feature request, and a set of held-out executable test cases, edit the repository so that the test cases pass.

Our work moves one step further along the same trajectory, by introducing a drastically more challenging SE benchmark for future assistants. Specifically, we target *crash resolution in the Linux kernel* [Lin]: given a state of the Linux codebase, a crash report, and the crash-inducing input, the target is to repair the codebase such that the input no longer triggers a crash. To that effect, we build an execution environment, KGYM, and corresponding benchmark, KBENCHSYZ.

Why Linux? The Linux Kernel spans over 20M lines of code spread across 50k files. It has been in open-source development for decades and is deployed on billions of devices worldwide, including cloud infrastructures, desktops, and over three billion active Android devices [And]. Although the criticality of Linux itself justifies a benchmark built around it, KBENCHSYZ also tests LLM assistants on new and generalizable SE skills beyond what is available today:

- **Low level:** Linux is a systems codebase written in a mixture of C, Assembly (for multiple hardware architectures, like x86, ARM, etc.), Bash, and Rust, sometimes intermingled in the same file (e.g., in Assembly embedded in C). As a result, the implementation must be hardware-aware and memory-safe, in contrast to userspace code (often hardware-agnostic) and code in managed languages such as Python (the runtime abstracts away memory and hardware details).
- **Concurrent:** Linux code is highly concurrent and non-deterministic, with many kernel bugs caused by hard-to-reproduce thread interleavings, leading to deadlocks, race conditions, and atomicity violations (“Heisenbugs”). To resolve such bugs, the model must be able to learn and reason about the different interleaving schedules across concurrent threads. Moreover, a corresponding benchmark platform must work with *flaky* test oracles—the bug is sometimes observed, but not always—unlike existing benchmarks, which rely on deterministic oracles.
- **Ambiguous Intent:** Unlike application-level SE tasks that start with an NL description of a problem, the root cause in a crash report is often unknown, hard to reproduce, and must be identified before it can be resolved. This makes for a challenging task, both in terms of ambiguity and the underlying dependence on myriad behaviors of the complex kernel.
- **Decentralized Development:** Linux development is highly decentralized; a recent version (v6.3) saw contributions from $\sim 2k$ developers, with 513k lines deleted and 644k lines added [RV6]. Such decentralized development is managed by splitting the kernel into subsystems, each with head maintainers. Consequently, each subsystem has unique coding conventions, including custom memory allocators, complex data structures, and specific coding templates.

KBENCHSYZ consists of 279 Linux-kernel bug-resolution samples. Each consists of (i) a commit-id that specifies a kernel code-base exhibiting the bug crash; (ii) a crash report containing one (or more) crash stack traces; (iii) a reproducer (i.e., a crashing test input program); (iv) a developer-written and vetted patch that, when applied to the kernel code-base, fixes the root cause of the crash and results in an operational kernel; and (v) compilation and execution configuration files for the above. Additionally, it provides detailed email discussions between kernel developers leading to a bug’s resolution. The samples are diverse, covering multiple critical subsystems, exhibiting various crash types, and requiring fixes from a single line to many lines across multiple functions and files.

KBENCHC. We have also curated and released a larger dataset of 504 Linux-kernel bugs. KBENCHC and KBENCHSYZ differ in the artifact used to reproduce the kernel bugs. While KBENCHSYZ uses a *syz* reproducer file (explained in Section 2) to reproduce the bugs, KBENCHC uses a C code snippet that has been derived (translated) from the original *syz* reproducer.

For the remainder of this paper however, we describe and report results on KBENCHSYZ.

³<https://evalplus.github.io/leaderboard.html>

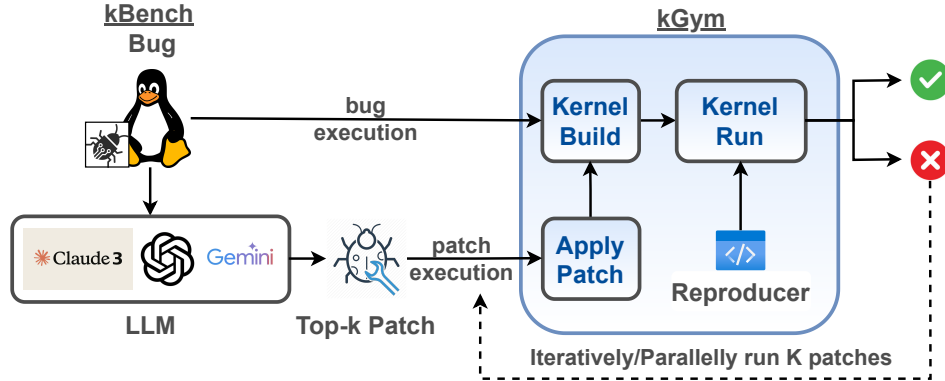


Figure 1: KGym Pipeline. Input to KGym is a KBENCHSYZ bug consisting of a kernel crash and a crash reproducer file. To reproduce the bug, KGym compiles the buggy kernel version and runs the reproducer file. Next, the LLM is prompted with the kernel bug (along with the crash trace) to generate potential patch(es). Each code patch is given to KGym, which then applies the patch to the buggy kernel version, compiles the entire kernel, and subsequently executes a reproducer file to check if the bug has been successfully resolved.

KGym provides an execution platform for ML-assisted SE to address challenges in KBENCHSYZ. It is scalable, user-friendly, and capable of (a) compiling hundreds of Linux kernel versions, (b) applying patches to buggy kernels, and (c) executing bug reproducers to either replicate a Linux kernel bug or confirm crash resolution after a patch. A sample end-to-end run of KGym is shown in Figure 1. As depicted, KGym facilitates a typical debug-patch-test cycle, where given a crash report an LLM is called to generate a code patch (or Top-K patches). KGym then applies the patch to the buggy kernel, runs the reproducer, and returns results: which can be another crash or a successful resolution. Key features of KGym for KBENCHSYZ include parallel execution across VMs and replicated test execution to manage non-determinism. Equipped with parallel execution, KGym can run hundreds to thousands of iterations of this loop within a day with limited resources, thus supporting further research in AI-assisted SE and low-level systems software.

Using KGym, we first reproduced all 279 bugs in KBENCHSYZ and then used LLMs in the pipelines to fix them. In this process, we ran over 17k kernel jobs using both open-source and state-of-the-art LLMs. In both RAG-based assisted (5.38%) and unassisted (0.72%) settings, our results show that even the best LLMs perform poorly on Linux kernel crash resolution, suggesting that KBENCHSYZ is poised to establish itself as the next frontier benchmark for LLM-assisted SE.

In what follows we list the different kernel bug components, provide details about KGym, describe how we collected KBENCHSYZ, and present initial crash-resolution results using popular LLMs.

2 Background: Continuous Testing via Syzkaller in Syzbot

To enhance Linux kernel security, the security community has developed numerous fuzzing tools over the past decade [Syz, Tri, Schumilo et al., 2017, Kim et al., 2020]. These tools automatically mutate and prioritize inputs to test the kernel, aiming to find bugs that developers can eventually resolve. We choose Syzkaller [Syz] to construct KBENCHSYZ as it is a widely-used open-source testing service for the Linux Kernel, where developers post, discuss, and fix kernel bugs. To date, more than 5k Syzkaller-detected kernel bugs have been reported and fixed, far surpassing the total bugs detected in the two decades before Syzkaller’s inception in 2016 [CVE].

Syzkaller generates inputs resembling user-space programs by mutating a domain-specific language (DSL) called *syz* and can optionally translate this into a C program. Thus, the input to a kernel is itself a program containing a sequence of up to 10 Linux kernel system calls. The specifics of the *syz* DSL and how Syzkaller mutates the input are beyond the scope of this paper; what is relevant is that the input to each KBENCHSYZ sample is a user-space program produced by Syzkaller, which we also refer to as the *Reproducer*. For the bugs in KBENCHCHC, the input to each sample is the C program translation of the Syzkaller user-space program. Unlike the *syz* program which is relatively short, the C translation can be arbitrarily long as it directly depends on the output of the translation procedure.

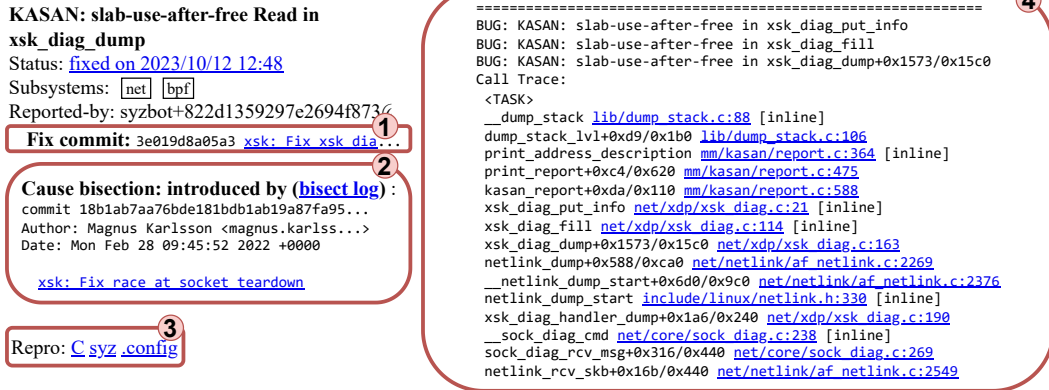


Figure 2: A sample kernel bug from Syzkaller [Bug]

Syzbot is an open-source platform that continuously runs Syzkaller on numerous kernels spanning multiple versions, architectures, and branches; testing them against various fault detectors. These detectors range from simple ones that detect kernel deadlocks or crashes (a.k.a., kernel “panic”, when the kernel reaches an irrecoverable fault state) to complex ones looking for high-priority assertion violations. Many such detectors are called *sanitizers* [Stepanov and Serebryany, 2015, Con, Serebryany et al., 2012, Add], which typically look for concurrency and memory-safety issues. For instance, KASAN, the Kernel Address Sanitizer [Serebryany et al., 2012], detects memory corruption such as out-of-bounds reads and use-after-free accesses. Whenever a fault detector is triggered during a Syzkaller run, a kernel crash report is posted on a public Syzbot site (Figure 2). Kernel developers discuss the report, propose fixes, and the crash is considered resolved when the reproducer no longer triggers the crash and a maintainer accepts the fix.

We collect KBENCHSYZ samples (as shown in Figure 2) from the reported and fixed bugs on Syzbot. More specifically, for each bug, we collect

- i. $\text{Commit}_{\text{bug}}$: the specific kernel commit id exhibiting the crash.
- ii. Config : a file that specifies options and flags needed to correctly compile the Linux kernel.
- iii. Reproducer : the bug reproducer (③ in Figure 2) that triggers the crash.
- iv. $\text{Commit}_{\text{fix}}$ and Fix (gold fix): fix commit id and developer patch that resolves the bug (①).
- v. $\text{Crash}_{\text{bug}}$: the crash report and stack traces generated at the commit id $\text{Commit}_{\text{bug}}$ (④).
- vi. Bisect : a cause-bisection commit identifying the first commit that exposed the bug (available for $\sim 20\%$ of bugs) (②).
- vii. Email : email discussions of developers about the bug. This is included as auxiliary information for bug localization, explanation, and repair research.

3 KGYM: A Scalable Platform for Kernel Bug Reproduction and Resolution

KGYM is a scalable, flexible, extensible, and user-friendly platform for research using LLM-assisted tools on Linux Kernel SE problems. Below, we list the inputs to KGYM and the different actions that KGYM provides to a user (here “user” can refer to an AI agent) to apply patches, build kernels, and run reproducers (Figure 1). We highlight two important functionalities of KGYM, Kbuilder and Kreproducer. For an in-depth explanation of KGYM’s architecture, see Appendix 3.

Inputs: From the features discussed in Section 2, we only need the commit id, the Config , and the Reproducer to reproduce a bug using KGYM. Additionally, we provide a crash report to the LLM to help it generate a patch. Using these inputs, KGYM can perform the list of actions mentioned below.

Build: For kernel crash resolution, we must first enable the building of kernels at specified commit ids. We provide a kernel-building API supported by Kbuilder, that focuses on compiling a kernel based on user specifications. These include a *git-url*, a *commit-id* (e.g., $\text{Commit}_{\text{bug}}$), a *kernel-config* (Config), a *compiler*, a *linker*, a *hardware architecture* (currently amd64), and a *userspace image* (options: buildroot, debian-bullseye, debian-buster, debian-stretch).

Reproduce-Bug: Once the user builds a kernel, the next step is to run the Reproducer to generate the crash report. We provide a bug-reproducing API supported by Kreproducer. This API requires (i) a pre-compiled disk image (from Build) and (ii) a Reproducer file. Kreproducer launches a VM with the image, monitors the reproducer’s execution, and collects kernel panic information if a crash occurs. Thus, using Reproduce-Bug, we can generate and collect the crash report for the Linux kernel bug. However, since many bugs are non-deterministic, running the reproducer once may not suffice. A Parallel-Reproduce action launches multiple VMs to run Reproduce-Bug in parallel, increasing the chances of reproducing the kernel crash.

Retrieve-File: After obtaining the crash report, the next steps are to (i) retrieve relevant code files from the Linux codebase, (ii) inspect these files, and (iii) suggest a patch. The Retrieve-File action fetches files from the Linux codebase at a specific commit-id by checking out the correct commit and retrieving the specified files.

Patch: The input prompt to the LLM is constructed using the crash report and retrieved files. The LLM then generates a fix, which can be applied to the codebase at the specified commit-id. To check for crash resolution, the user must first apply the fix, recompile the Linux kernel, and then re-run the Reproducer. The Patch action facilitates this by taking a *patch* argument specified in the git diff format in addition to all the Build action arguments. The Patch action applies the patch and compiles the kernel. The user can then use this compiled kernel with the Reproduce-Bug action. If the Reproducer does not crash the kernel within 10 minutes, the bug is considered resolved.

Kernel-Log: For future works that monitor the Linux kernel environment, we provide the Kernel-log action. When invoked, Kernel-log downloads the Kernel’s ring buffer (dmesg⁴ output) for inspection after applying and running a patch. Analyzing kernel log changes is challenging due to its verbosity, often containing hundreds of thousands of lines. Although we believe this log will become crucial in kernel crash resolution, we leave this as a future research area.

4 KBENCHSYZ

We use the KGYM system explained in Section 3 to curate KBENCHSYZ, a dataset of Linux kernel bugs and fixes. We then use this dataset to benchmark the efficacy of state-of-the-art LLMs in solving bugs in production-ready software. In what follows, we explain how we derive a gold standard subset of bugs from the Syzkaller dataset and then delve into the characteristics of the benchmark itself.

Notion of a Fix: We follow Syzkaller and deem a patch as a valid bug fix if, upon application of the patch, the kernel remains functional without a crash, after executing the Reproducer.

Retrieving Kernel Versions to Apply Fixes ($\text{Commit}_{\text{parent}}$): For many bugs, there can be thousands of commits between $\text{Commit}_{\text{bug}}$ and $\text{Commit}_{\text{fix}}$ because patches for old bugs are often submitted to the current latest kernel version. Hence, to verify if a patch successfully resolves a crash, we must first compute the last commit before $\text{Commit}_{\text{fix}}$ where the bug is still reproducible. This is $\text{Commit}_{\text{parent}}$, which is the parent commit immediately before $\text{Commit}_{\text{fix}}$ in the git tree.

Filtering a Gold Standard: For each bug, we collect $\text{Commit}_{\text{bug}}$, Config, Reproducer, $\text{Commit}_{\text{fix}}$, Fix, and $\text{Commit}_{\text{parent}}$ (where we will apply the fix). We filter the bugs using three criteria: (1) The kernel crashes when running Reproducer on $\text{Commit}_{\text{bug}}$, (2) The kernel crashes when running Reproducer on $\text{Commit}_{\text{parent}}$, and (3) The kernel does not crash when running Reproducer on $\text{Commit}_{\text{fix}}$. These checks ensure each data point is a valid reproducible bug with a demonstrable fix.

Experiment Caveat: In Section 5, we perform all crash resolution experiments on $\text{Commit}_{\text{parent}}$ to allow for a qualitative comparison of the LLM’s suggested patch against the actual Fix. Therefore, we provide the crash report generated at $\text{Commit}_{\text{parent}}$ as part of the input prompt to the LLM. Using KGYM, we run every bug in KBENCHSYZ and collect $\text{Crash}_{\text{parent}}$, the crash report observed when running the Reproducer on $\text{Commit}_{\text{parent}}$. Consequently, each data point in KBENCHSYZ is characterized by a seven-tuple: ($\text{Commit}_{\text{bug}}$, Config, Reproducer, $\text{Commit}_{\text{fix}}$, $\text{Commit}_{\text{parent}}$, $\text{Crash}_{\text{parent}}$, Fix). It is important to note that crash resolution can still be attempted on $\text{Commit}_{\text{bug}}$. But due to the thousands of commits between $\text{Commit}_{\text{bug}}$ and $\text{Commit}_{\text{parent}}$, the correct solution for $\text{Commit}_{\text{bug}}$ may differ vastly from the Fix. In the following section, we perform some quantitative studies of KBENCHSYZ to better understand the characteristics of this benchmark.

⁴<https://en.wikipedia.org/wiki/Dmesg>

4.1 Characteristics of the KBENCHSYZ

Table 1: Kernel Versions

Kernel Version	Bugs
4.x.x (2015 onwards)	26
5.x.x (2019 onwards)	141
6.x.x (2022 onwards)	112

Table 2: Fix Types

Fix Type	Bugs
Single Line	33
Single Function but Multiline	145
Multi Function but Single File	57
Multi Files	44

Table 3: Line/File Statistics

Data Type	Avg / Max
GF Lines Changed	14.27 / 147
GF Files Changed	1.28 / 7
Crash _{parent} Lines	84.3 / 624

Kernel Versions: The Linux kernel continuously evolves with contributions from thousands of developers worldwide, resulting in major releases every 3 to 5 years. Additionally, each major version is supported with updates for almost 10 years after the release. Capturing this diversity is important in our dataset. Table 1 shows the distribution of kernel versions in KBENCHSYZ, which includes a range of versions from the past 10 years (versions 4 to 6).

Fix types: To measure performance on varied types of fixes, it is important to ensure fix diversity in the KBENCHSYZ. Hence, we consciously include kernel bugs with varied fix sizes—from smaller single-line fixes to larger multi-file fixes. In Table 2, we show a detailed distribution of our dataset.

Line statistics: In addition to fix types, it is important to consider the line/file-level statistics of the gold fixes (GF) and the kernel crashes in the dataset. In Table. 3, we show the distribution of these statistics across the Dataset. As shown, the average lines changed in a GF is 14.27 (maximum of 147), and the average files changed in a GF is 1.28 (maximum of 7). Similarly, we observe that the kernel crash report is very verbose with an average of 84.3 and a maximum of 624 lines respectively.

Fix Distribution Over Time: To better understand the temporal distribution of fixes in KBENCHSYZ, we study the number of Linux bug fixes accepted each year from 2018 to 2023. As shown in Table 4, KBENCHSYZ has temporal diversity with many bugs from recent as well as past years.

Git Tree: Syzkaller has discovered bugs in numerous git trees of Linux. However, for the initial version of KBENCHSYZ, we stick to the mainline git tree and will eventually expand to other trees.

Subsystem Distribution: The Linux kernel is broken down into individual subsystems to streamline maintenance and development. Each kernel subsystem is actively maintained by a unique team of kernel experts. As a result, KBENCHSYZ should ideally have diverse bugs spanning multiple subsystems. As shown in Figure 3, KBENCHSYZ has bugs from 72 subsystems with net (network), usb and fs (filesystem) being the three biggest categories.

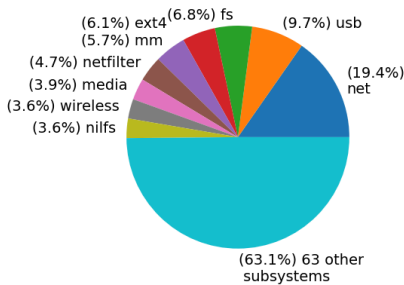


Figure 3: Subsystem Distribution

Table 4: Fix Distribution Over Time

Year	Number of Fixes
2023	79
2022	82
2021	34
2020	44
2019	20
2018	20

Table 4: Fix Distribution Over Time

5 Experiments

We conduct extensive baseline experiments to benchmark state-of-the-art LLMs on KBENCHSYZ. We describe how we construct the input prompt, list the open and closed LLMs used, outline the two testing settings, and present a qualitative and quantitative analysis of the results.

5.1 Models

Closed LLMs: We conduct experiments on state-of-the-art closed LLMs like GPT-3.5 Turbo, GPT-4 Turbo, Claude-3 Sonnet, and Gemini-1.5 Pro. For GPT-3.5 Turbo, we use a maximum context length of 16k tokens. For more powerful models like GPT-4 Turbo, Gemini-1.5 Pro, and Claude-3 Sonnet, we use a maximum context size of 50k tokens to stay within budget constraints.

Open LLMs: We also experiment with the Llama series of open-source instruction-tuned LLMs like Code Llama-7b-Instruct, Code Llama-13b-Instruct, Code Llama-34b-Instruct, and Llama-3-8B-Instruct. To stay within resource constraints, we restrict ourselves to a maximum context length of 16k tokens.

5.2 Input Prompt

To generate viable kernel patches, we provide meaningful context in the LLM’s input prompt. For each bug in KBENCHSYZ, the prompt includes `Crashparent` and relevant C files (Section A.3). Since Linux Kernel files can be thousands of lines long, prompts often exceed the maximum context lengths of LLMs. Therefore, we run experiments on smaller subsets of KBENCHSYZ, detailed in Section 5.3.

5.3 Evaluation Settings

An important part of the input prompt is a set of C files relevant to the crash report. Given the Linux kernel’s vast size, selecting the most relevant files is challenging. Following SWE-Bench [Jimenez et al., 2024], we use a retrieval-based system for this task and evaluate each LLM in two settings:(1) oracle retrieval and (2) sparse retrieval. It is important to note that in both settings, we limit the kernel crash report to a maximum of 10k tokens to keep enough space for the relevant C files.

Oracle Retrieval: In this setting, we parse the actual developer `Fix` and collect the modified files. Each modified file is included in the prompt, and the LLM is asked to generate a patch for these files. This assisted setting makes the task easier, but we are forced to skip the bug if all Oracle files do not fit into a single prompt. This reduces the number of bugs to 117 for models with a 16k context size (e.g., GPT-3.5 Turbo and Llama models) and 228 for models with a 50k context size (e.g., GPT-4 Turbo, Claude-3 Sonnet, and Gemini-1.5 Pro).

Sparse Retrieval: In the unassisted setting, the bug is first localized to a set of C files before the LLM generates a patch. This localization can be done using many techniques. Dense retrieval mechanisms are ill-suited [Jimenez et al., 2024] because of the sheer scale of the Linux kernel (> 20M lines and > 50k files). Hence, using `Crashparent` as the key, we adopt a sparse retrieval method like BM25 to retrieve the top 3 files to modify. Once we get the top 3 files, we add as many files as possible to the input prompt without exceeding the context limit. However, we intentionally skip a kernel bug if we cannot fit a single file. For models with a context length of 16k, the number of bugs is reduced to 227, and for a longer context length of 50k, we get 275 bugs. Please refer to Table 10 in the Appendix for a tabular view of the model variants against their respective KBENCHSYZ subsets.

BM25 Efficacy: To evaluate BM25, we compare its retrieval predictions against the set of Oracle files. As shown in Table 5, as we retrieve more predictions from BM25 by increasing K from 3 to 20, the number of samples for which BM25 returns a superset of the oracle files increases from 1.76% to 9.69% for a 16k context length and from 2.91% to 10.54% for a 50k context length. As evident from Table 5, there is a lot of scope to improve bug localization using a given kernel crash report. However,

these results are unsurprising, because if we set K to 3 and assume a single Oracle file, the probability of correctly including the Oracle file in 3 random choices from the 50k files in the Linux kernel is 0.006. Thus, in contrast to random guessing, BM25 does a reasonable job.

Table 5: BM25 Recall for different values of Top-K and context lengths. All, Any and None denote complete, partial, and no overlap with oracle files respectively.

Top K	BM25 Recall	
	16K	50K
3	All / Any / None 1.76 / 0.00 / 98.24	All / Any / None 2.91 / 0.00 / 97.09
5	3.96 / 0.44 / 95.6	5.10 / 0.36 / 94.54
10	6.61 / 0.00 / 93.39	7.64 / 0.00 / 92.36
20	9.69 / 0.44 / 89.87	10.54 / 0.36 / 89.10

5.4 Quantitative Analysis of Patch Generation

Querying LLMs: To stay within budget and API constraints, we query each LLM differently. For GPT-3.5 Turbo and GPT-4 Turbo APIs, we ask for the top-10 likely patches. By extracting 10 outputs (instead of 1), the total cost increases by only 20-30% as the long input context exhausts most of the budget. The Gemini-1.5 Pro API does not provide a parameter for multiple outputs, but as it is currently free to use, we query Gemini 10 times with the same input tokens. There is also no such parameter for the paid Claude-3 Sonnet API, so we conduct experiments with a single output to limit costs. As such, the Claude API metrics should likely improve if 10 outputs are considered.

Compute: To run the crash resolution experiments using KGYM at scale, we employ 11 VMs hosted on Google Cloud. Each VM is a `c2-standard-30` Google Compute Engine (GCE) instance.

Table 6: Patch Application and Bug Solve Rates using state-of-the-art LLMs. CL stands for CodeLlama and L3 stands for LLama-3. All % numbers are calculated for the entire 279 bugs in KBENCHSYZ. We ran over 17,000 kernel jobs using KGYM to quantify these results.

Top-N	Patch Results	GPT-3.5 Turbo	CL 7b	CL 13b	CL 34b	L3 8B	GPT-4 Turbo	Claude 3 Sonnet ⁵	Gemini 1.5 Pro
		(1, 10)	(1)	(1)	(1)	(1)	(1, 10)	(1)	(1, 10)
Oracle	Apply %	(1.43, 15.41)	9.68	0.72	15.41	0.36	(20.07, 56.99)	27.60	(22.22, 45.52)
	Solve %	(0, 1.08)	0	0	0	0	(1.08, 5.38)	1.79	(0.72, 3.58)
BM25	Apply %	(13.26, 40.86)	20.79	0.72	40.14	1.08	(15.77, 55.20)	28.67	(12.19, 24.37)
	Solve %	(0.36, 0.36)	0	0	0	0	(0, 0.72)	0	(0, 0)

Patch Application Rate: As part of the input prompt, we ask the LLM to generate a `git diff` patch for KGYM to apply to the codebase. However, we observe that current state-of-the-art LLMs often struggle to generate *syntactically valid* patches with the correct `diff` structure. This issue has also been noted in other works like SWE-Bench [Jimenez et al., 2024]. Table 6 shows the patch application rate (Apply %) for each LLM in both the Oracle and BM25 settings to illustrate the prevalence of this problem. Amongst the 50k context models (GPT-4 Turbo, Claude-3 Sonnet, and Gemini-1.5 Pro), GPT-4 Turbo achieves the highest application rate as it generates well-formed patches for more than half the bugs in both the Oracle (56.99%) and BM25 settings (55.2%). For the remaining 16k context models, we notice the highest Apply % for GPT-3.5 Turbo in both settings (15.41% and 40.86%).

Bug Solve Rate: In addition to the patch application rate, we also measure % of *semantically valid* patches, i.e., the % of bugs solved when successfully applying the patch (Solve %). Amongst the 50k context models, GPT-4 Turbo has the highest solve rate of 5.38%, solving 15 bugs in the Oracle setting. However, in the BM25 setting, due to poor retrieval performance, only GPT-4 Turbo has a non-zero solve rate of 0.72% indicating that more research is needed to improve kernel bug localization and resolution. For the 16k context models, GPT-3.5 Turbo has the highest solve rates of 1.08% and 0.36% in the Oracle and BM25 settings respectively. Unfortunately, the solve rates for all the Llama models are 0% in all scenarios.

Union: Upon inspecting all the correct LLM patches, we note 29 unique bug ids from a total of 36 solved bugs. Hence, combining the patches from all the models results in a solve rate of 10.39%.

Overall, we observe that state-of-the-art LLMs struggle to effectively resolve Linux kernel bugs due to the sheer complexity and scale of the problem. As a result, we believe that there is a lot of scope for research to make LLMs effective in this domain. In the following section, we will qualitatively analyze an example patch from GPT-4 Turbo and compare this to the actual `Fix`.

5.5 Qualitative Analysis of Patch Generation

Figure 4 shows an example of a memory leak bug in KBENCHSYZ. The crash report (left) includes a stack trace with `cinergyt2_frontend_attach` highlighted in red, which is the buggy function that is modified in the `Fix`. On the right, we compare the actual `Fix` by a developer with a successful patch suggested by GPT-4 Turbo. The model’s patch correctly localizes the bug but is less nuanced and safe than the developer’s solution. The developer’s fix ensures memory safety and follows coding conventions, while the model’s patch uses `kfree`, which can cause issues if the memory was not

⁵Top-10 results for Claude-3-Sonnet were skipped due to budget constraints

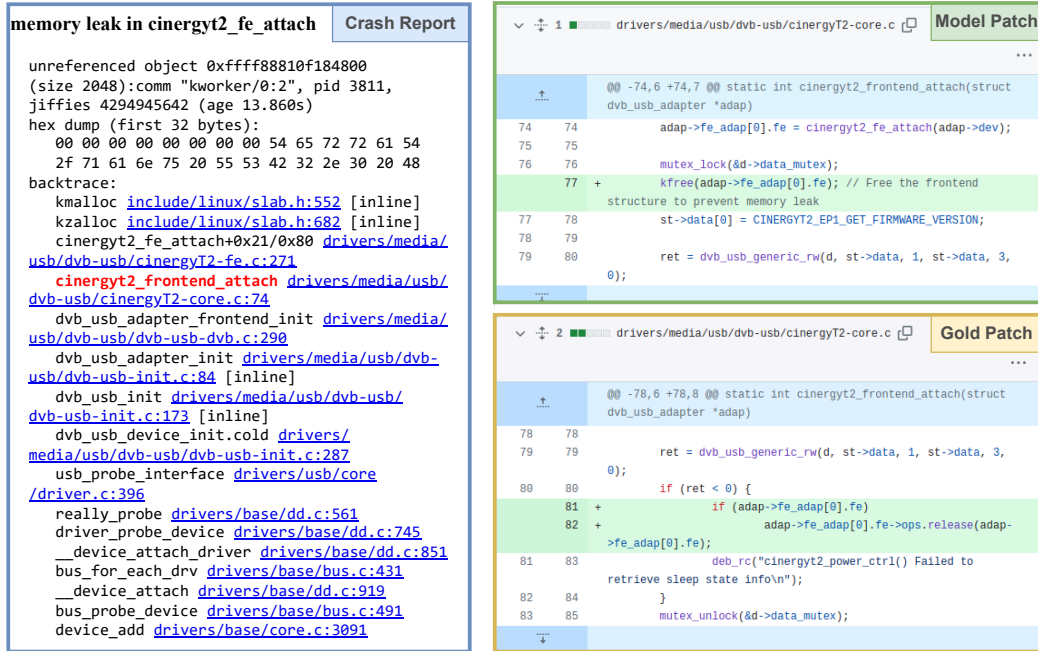


Figure 4: A sample bug patch using GPT-4 Turbo. The left figure shows a stack trace with the buggy function highlighted in red. The right figure compares a successfully generated patch by GPT-4 Turbo vs a human developer. The developer solution first confirms that `adap->fe_adap[0].fe` is not null and then uses the function pointer field `ops.release` to deallocate the structure safely using a custom memory deallocator. In contrast, the model uses `kfree` in the generated patch to deallocate the object which implicitly assumes that the object was allocated memory using `kmalloc`.

allocated with `kmalloc`. Despite its shortcomings, the model’s patch can expedite debugging by highlighting the root cause, guiding the developer in composing a more accurate fix, thereby speeding up kernel crash resolution.

6 Related Work

Code Modeling and ML for SE. Recent advancements in code LMs have made program synthesis a reality [Guo et al., 2022, Ahmad et al., 2021, Wang et al., 2021, Feng et al., 2020]. Many efforts have also scaled these advancements to build models that show amazing code comprehension and completion capabilities [Ila, Rozière et al., 2024, Nijkamp et al., 2023a,b, Fried et al., 2023, Chen et al., 2021]. Subsequently, many works have adapted code LMs to assist in various SE tasks like testing [Xia et al., 2024, Wang et al., 2024, Kang et al., 2023], program repair [Dinh et al., 2023, Gao et al., 2022], commit generation [Liu et al., 2023b], and pull request reviews [Li et al., 2022]. Program repair is the closest research area to this work. However, previous works have not explored program repair in the context of massive systems-level repositories. We believe this is partly because performing large-scale experiments on these codebases is very challenging. Hence, we hope that KGYM will spur research at the intersection of ML and systems-level code.

Benchmarking. The most commonly evaluated application of Code LLMs is code generation. As a result, there are a plethora of code completion benchmarks. Most benchmarks including HumanEval [Chen et al., 2021] and others [CodeGeeX, 2022, Austin et al., 2021, Athiwaratkun et al., 2023, Cassano et al., 2023, Hendrycks et al., 2021, Lu et al., 2021, Puri et al., 2021, Clement et al., 2021, Ding et al., 2023a, Wang et al., 2023, Lu et al., 2022] mainly assess code completion by providing in-file context, i.e., the LLM prompts only contain code from a single file. More recent works have introduced tougher repository-level benchmarks [Shrivastava et al., 2023, Ding et al., 2022, Pei et al., 2023, Zhang et al., 2023, Ding et al., 2023b, Jimenez et al., 2024]. Among these, SWE-bench (Jimenez et al. [2024]) is the closest related work as it concentrates on repository-level program repair.

However, unlike SWE-bench, KBENCHSYZ focuses on low-level systems code, not generic userspace code like Python libraries. Additionally, a sample KBENCHSYZ problem has a code context scale that is 50 times the size of the largest SWE-bench instance. Hence, we believe that progress made on KBENCHSYZ would reflect advancements in the real-world crash resolution capabilities of ML models.

7 Limitations

Time Intensive Experiments. Due to the large size of the Linux kernel, compilation and linking of $\sim 50k$ files takes a significant amount of time. Using a `c2-standard-30` machine, the compilation process takes 15 to 20 minutes. After this, if a patch is correct, the reproducer runs for 10 minutes, and if incorrect, the kernel crashes within a couple of minutes. Thus, the total feedback time, after patch application, ranges from 17 to 30 minutes. As such, running kernel experiments is time intensive.

Single Test Reproducer. As KGYM builds upon Syzkaller, it uses a single Reproducer to check if the crash goes away. As a result, it is possible for an LLM to generate a patch that may work for crash resolution but may significantly alter code functionality. Thus after the reproducer check, extensive testing maybe required to ensure that the kernel functions correctly. This can be done by using tools like Linux Testing Project⁶ or Linux Kernel Selftests⁷.

8 Conclusion

In this work, we introduce KBENCHSYZ (and KBENCHC), a new challenging SE benchmark aimed at Linux kernel crash resolution. To effectively experiment on KBENCHSYZ, we also introduce KGYM, a platform to execute large-scale kernel experiments. To interact with KGYM, we also provide few simple APIs. Using KGYM, we run over 17k kernel jobs to report our initial baseline results that indicate poor performance even when using state-of-the-art LLMs. Thus, we conclude that there is adequate scope for research to improve crash resolution performance in massive production-ready systems-level codebases. We hope that by introducing KBENCHSYZ and KGYM, we spur more efforts that lower the barrier of entry to research at the intersection of machine learning and system software.

9 Acknowledgements

This work was partly supported by multiple Google Cyber NYC awards, a Columbia SEAS/EVPR Stimulus award and the following NSF awards - IIS 2221943, CCF 2313055, CCF 1845893, CCF 2107405.

References

Kernel address sanitizer. <https://www.kernel.org/doc/html/latest/dev-tools/kasan.html>.

Android. <https://blog.google/products/android/io22-multideviceworld>.

Syzkaller kasan use-after-free bug. <https://syzkaller.appspot.com/bug?extid=822d1359297e2694f873>.

Cvedetails. https://www.cvedetails.com/product/47/Linux-Linux-Kernel.html?vendor_id=33.

The kernel concurrency sanitizer (kcsan). <https://www.kernel.org/doc/html/latest/dev-tools/kcsan.html>.

Linux. <https://github.com/torvalds/linux>.

Linux 6.3. <https://lwn.net/Articles/929582/>.

⁶<https://linux-test-project.readthedocs.io/en/latest/>

⁷<https://docs.kernel.org/dev-tools/kselftest.html>

- Syzkaller. <https://github.com/google/syzkaller>.
- Trinity: Linux system call fuzzer. <https://github.com/kernelSlacker/trinity>.
- Llama3. <https://github.com/meta-llama/llama3>.
- Wasi Ahmad, Saikat Chakraborty, Baishakhi Ray, and Kai-Wei Chang. Unified pre-training for program understanding and generation. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2655–2668, Online, June 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.naacl-main.211. URL <https://aclanthology.org/2021.naacl-main.211>.
- Amazon. Amazon codewhisperer: Build applications faster and more securely with your ai coding companion. <https://aws.amazon.com/codewhisperer/>, 2023.
- Ben Athiwaratkun, Sanjay Krishna Gouda, Zijian Wang, Xiaopeng Li, Yuchen Tian, Ming Tan, Wasi Uddin Ahmad, Shiqi Wang, Qing Sun, Mingyue Shang, Sujan Kumar Gonugondla, Hantian Ding, Varun Kumar, Nathan Fulton, Arash Farahani, Siddhartha Jain, Robert Giaquinto, Haifeng Qian, Murali Krishna Ramanathan, Ramesh Nallapati, Baishakhi Ray, Parminder Bhatia, Sudipta Sengupta, Dan Roth, and Bing Xiang. Multi-lingual evaluation of code generation models. In *The Eleventh International Conference on Learning Representations, 2023*. URL <https://openreview.net/forum?id=Bo7eeXm6An8>.
- Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, et al. Program synthesis with large language models. *ArXiv preprint*, abs/2108.07732, 2021. URL <https://arxiv.org/abs/2108.07732>.
- Federico Cassano, John Gouwar, Daniel Nguyen, Sydney Nguyen, Luna Phipps-Costin, Donald Pinckney, Ming-Ho Yee, Yangtian Zi, Carolyn Jane Anderson, Molly Q Feldman, Arjun Guha, Michael Greenberg, and Abhinav Jangda. Multipl-e: A scalable and polyglot approach to benchmarking neural code generation. *IEEE Transactions on Software Engineering*, 49(7):3675–3691, 2023. doi: 10.1109/TSE.2023.3267446.
- 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. Evaluating large language models trained on code, 2021.
- Colin Clement, Shuai Lu, Xiaoyu Liu, Michele Tufano, Dawn Drain, Nan Duan, Neel Sundaresan, and Alexey Svyatkovskiy. Long-range modeling of source code files with eWASH: Extended window access by syntax hierarchy. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 4713–4722, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.emnlp-main.387. URL <https://aclanthology.org/2021.emnlp-main.387>.
- CodeGeeX, 2022. <https://github.com/THUDM/CodeGeeX>.
- Hantian Ding, Varun Kumar, Yuchen Tian, Zijian Wang, Rob Kwiatkowski, Xiaopeng Li, Murali Krishna Ramanathan, Baishakhi Ray, Parminder Bhatia, Sudipta Sengupta, et al. A static evaluation of code completion by large language models. *arXiv preprint arXiv:2306.03203*, 2023a.
- Yangruibo Ding, Zijian Wang, Wasi Uddin Ahmad, Murali Krishna Ramanathan, Ramesh Nallapati, Parminder Bhatia, Dan Roth, and Bing Xiang. Cocomic: Code completion by jointly modeling in-file and cross-file context. *arXiv preprint arXiv:2212.10007*, 2022. URL <https://arxiv.org/abs/2212.10007>.

- 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. Crosscodeval: A diverse and multilingual benchmark for cross-file code completion. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2023b. URL <https://arxiv.org/pdf/2310.11248.pdf>.
- Tuan Dinh, Jinman Zhao, Samson Tan, Renato Negrinho, Leonard Lausen, Sheng Zha, and George Karypis. Large language models of code fail at completing code with potential bugs, 2023.
- Zhangyin Feng, Daya Guo, Duyu Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, and Ming Zhou. CodeBERT: A pre-trained model for programming and natural languages. In Trevor Cohn, Yulan He, and Yang Liu, editors, *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1536–1547, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.findings-emnlp.139. URL <https://aclanthology.org/2020.findings-emnlp.139>.
- Daniel Fried, Armen Aghajanyan, Jessy Lin, Sida Wang, Eric Wallace, Freda Shi, Ruiqi Zhong, Scott Yih, Luke Zettlemoyer, and Mike Lewis. InCoder: A generative model for code infilling and synthesis. In *The Eleventh International Conference on Learning Representations*, 2023. URL <https://openreview.net/forum?id=hQwb-1bM6EL>.
- Xiang Gao, Yannic Noller, and Abhik Roychoudhury. Program repair, 2022.
- GitHub. Github copilot: Your ai pair programmer. <https://copilot.github.com/>, 2021.
- Daya Guo, Shuai Lu, Nan Duan, Yanlin Wang, Ming Zhou, and Jian Yin. Unixcoder: Unified cross-modal pre-training for code representation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7212–7225, 2022.
- Dan Hendrycks, Steven Basart, Saurav Kadavath, Mantas Mazeika, Akul Arora, Ethan Guo, Collin Burns, Samir Puranik, Horace He, Dawn Song, and Jacob Steinhardt. Measuring coding challenge competence with apps. *NeurIPS*, 2021.
- Carlos E. Jimenez, John Yang, Alexander Wettig, Shunyu Yao, Kexin Pei, Ofir Press, and Karthik Narasimhan. Swe-bench: Can language models resolve real-world github issues?, 2024.
- Sungmin Kang, Juyeon Yoon, and Shin Yoo. Large language models are few-shot testers: Exploring llm-based general bug reproduction, 2023.
- Kyungtae Kim, Dae R. Jeong, Chung Hwan Kim, Yeongjin Jang, Insik Shin, and Byoungyoung Lee. Hfl: Hybrid fuzzing on the linux kernel. *Proceedings 2020 Network and Distributed System Security Symposium*, 2020. URL <https://api.semanticscholar.org/CorpusID:211267895>.
- Zhiyu Li, Shuai Lu, Daya Guo, Nan Duan, Shailesh Jannu, Grant Jenks, Deep Majumder, Jared Green, Alexey Svyatkovskiy, Shengyu Fu, and Neel Sundaresan. Automating code review activities by large-scale pre-training, 2022.
- Jiawei Liu, Chunqiu Steven Xia, Yuyao Wang, and Lingming Zhang. Is your code generated by chatgpt really correct? rigorous evaluation of large language models for code generation, 2023a.
- Shangqing Liu, Yanzhou Li, Xiaofei Xie, and Yang Liu. Commitbart: A large pre-trained model for github commits, 2023b.
- Shuai Lu, Daya Guo, Shuo Ren, Junjie Huang, Alexey Svyatkovskiy, Ambrosio Blanco, Colin Clement, Dawn Drain, Daxin Jiang, Duyu Tang, Ge Li, Lidong Zhou, Linjun Shou, Long Zhou, Michele Tufano, MING GONG, Ming Zhou, Nan Duan, Neel Sundaresan, Shao Kun Deng, Shengyu Fu, and Shujie LIU. CodeXGLUE: A machine learning benchmark dataset for code understanding and generation. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 1)*, 2021. URL <https://openreview.net/forum?id=61E4dQXaUcb>.

- Shuai Lu, Nan Duan, Hojae Han, Daya Guo, Seung-won Hwang, and Alexey Svyatkovskiy. ReACC: A retrieval-augmented code completion framework. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 6227–6240, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.431. URL <https://aclanthology.org/2022.acl-long.431>.
- Erik Nijkamp, Hiroaki Hayashi, Caiming Xiong, Silvio Savarese, and Yingbo Zhou. Codegen2: Lessons for training llms on programming and natural languages. *arXiv preprint arXiv:2305.02309*, 2023a. URL <https://arxiv.org/abs/2305.02309>.
- Erik Nijkamp, Bo Pang, Hiroaki Hayashi, Lifu Tu, Huan Wang, Yingbo Zhou, Silvio Savarese, and Caiming Xiong. Codegen: An open large language model for code with multi-turn program synthesis. In *International Conference on Learning Representations*, 2023b. URL https://openreview.net/forum?id=iaYcJKpY2B_.
- Simon Ott, Adriano Barbosa-Silva, Kathrin Blagec, Jan Brauner, and Matthias Samwald. Mapping global dynamics of benchmark creation and saturation in artificial intelligence. *Nature Communications*, 13(1), November 2022. ISSN 2041-1723. doi: 10.1038/s41467-022-34591-0. URL <http://dx.doi.org/10.1038/s41467-022-34591-0>.
- Hengzhi Pei, Jinman Zhao, Leonard Lausen, Sheng Zha, and George Karypis. Better context makes better code language models: A case study on function call argument completion. In *Proceedings of the Thirty-Seventh AAAI Conference on Artificial Intelligence and Thirty-Fifth Conference on Innovative Applications of Artificial Intelligence and Thirteenth Symposium on Educational Advances in Artificial Intelligence*, AAAI’23/IAAI’23/EAAI’23. AAAI Press, 2023. ISBN 978-1-57735-880-0. doi: 10.1609/aaai.v37i4.25653. URL <https://doi.org/10.1609/aaai.v37i4.25653>.
- Ruchir Puri, David S Kung, Geert Janssen, Wei Zhang, Giacomo Domeniconi, Vladimir Zolotov, Julian Dolby, Jie Chen, Mihir Choudhury, Lindsey Decker, Veronika Thost, Luca Buratti, Saurabh Pujar, Shyam Ramji, Ulrich Finkler, Susan Malaika, and Frederick Reiss. Codenet: A large-scale AI for code dataset for learning a diversity of coding tasks. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*, 2021. URL <https://openreview.net/forum?id=6vZVBkCDrHT>.
- 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. Code llama: Open foundation models for code, 2024.
- Sergej Schumilo, Cornelius Aschermann, Robert Gawlik, Sebastian Schinzel, and Thorsten Holz. kaff: Hardware-assisted feedback fuzzing for os kernels. In *USENIX Security Symposium*, 2017. URL <https://api.semanticscholar.org/CorpusID:12778185>.
- Kostya Serebryany, Derek Bruening, Alexander Potapenko, and Dmitriy Vyukov. Addresssanitizer: A fast address sanity checker. In *USENIX Annual Technical Conference*, 2012. URL <https://api.semanticscholar.org/CorpusID:11024896>.
- Disha Shrivastava, Hugo Larochelle, and Daniel Tarlow. Repository-level prompt generation for large language models of code. In Andreas Krause, Emma Brunskill, Kyunghyun Cho, Barbara Engelhardt, Sivan Sabato, and Jonathan Scarlett, editors, *Proceedings of the 40th International Conference on Machine Learning*, volume 202 of *Proceedings of Machine Learning Research*, pages 31693–31715. PMLR, 23–29 Jul 2023. URL <https://proceedings.mlr.press/v202/shrivastava23a.html>.
- Evgeniy Stepanov and Konstantin Serebryany. Memorysanitizer: Fast detector of uninitialized memory use in c++. In *2015 IEEE/ACM International Symposium on Code Generation and Optimization (CGO)*, pages 46–55, 2015. doi: 10.1109/CGO.2015.7054186.
- Junjie Wang, Yuchao Huang, Chunyang Chen, Zhe Liu, Song Wang, and Qing Wang. Software testing with large language models: Survey, landscape, and vision, 2024.

- Shiqi Wang, Zheng Li, Haifeng Qian, Chenghao Yang, Zijian Wang, Mingyue Shang, Varun Kumar, Samson Tan, Baishakhi Ray, Parminder Bhatia, Ramesh Nallapati, Murali Krishna Ramanathan, Dan Roth, and Bing Xiang. ReCode: Robustness evaluation of code generation models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 13818–13843, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.773. URL <https://aclanthology.org/2023.acl-long.773>.
- Yue Wang, Weishi Wang, Shafiq Joty, and Steven C.H. Hoi. CodeT5: Identifier-aware unified pre-trained encoder-decoder models for code understanding and generation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 8696–8708, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.emnlp-main.685. URL <https://aclanthology.org/2021.emnlp-main.685>.
- Chunqiu Steven Xia, Matteo Paltenghi, Jia Le Tian, Michael Pradel, and Lingming Zhang. Fuzz4all: Universal fuzzing with large language models, 2024.
- Fengji Zhang, Bei Chen, Yue Zhang, Jin Liu, Daoguang Zan, Yi Mao, Jian-Guang Lou, and Weizhu Chen. Repocoder: Repository-level code completion through iterative retrieval and generation. *arXiv preprint arXiv:2303.12570*, 2023. URL <https://arxiv.org/abs/2303.12570>.

A Appendix / supplemental material

A.1 KGYM: Background and Architecture

A.1.1 Background: Syzkaller

Despite Syzkaller’s many features, in practice, it is challenging to conveniently leverage Syzkaller to perform large-scale experiments on the Linux kernel. As a result, Syzkaller is often out of reach for the average code ML researcher but is routinely used by experienced kernel developers.

Syz-build and Syz-crush: With this in mind, we implement KGYM- a platform for ML-for-code researchers that is scalable and easy to use. We allow researchers to compile, execute, and monitor Linux kernels at scale by invoking a few simple APIs! To realize this goal, we first isolate and re-use some components of Syzkaller to build the basic blocks of KGYM. As shown in Figure 5, the two main components in KGYM are `Kbuilder` and `Kreproducer`. `Kbuilder` is designated the task of compiling a kernel when provided with a kernel config file and a specific Git commit id. When executing `Kbuilder`, we invoke Syzkaller’s `syz-build` utility - a robust tool developed in the Go language to compile various Linux kernel versions. `Kreproducer` on the other hand, executes a set of inputs (i.e., a reproducer file) on a pre-compiled kernel image. When we call `Kreproducer`, we internally invoke Syzkaller’s `syz-crush` module to run either C programs or Syzkaller’s domain-specific language (DSL) to reproduce identified bugs.

Scaling Kernel Compilation and Test Execution: The main advantage of using the KGYM system is that it can massively parallelize both the compilation of kernels as well as the execution of reproducer files. In our everyday experiments, we seamlessly run KGYM on 10 VMs, achieving a speed of 720 kernel compilations and reproducer executions within 24 hours. The ability to perform kernel experiments at this scale makes it practical and feasible for researchers to conduct tangible research at the intersection of LLMs and kernel bugs. In the following section, we delve into the fine architectural details of KGYM that make this possible.

A.1.2 Architecture

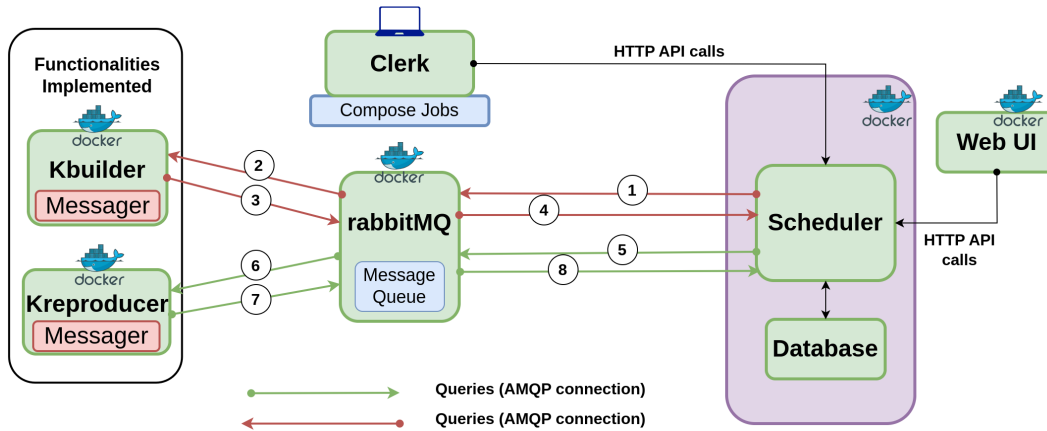


Figure 5: The KGYM Architecture

KGYM: KGYM is a scalable, flexible, extensible, and user-friendly platform for experimentation on the Linux Kernel. In what follows, we expand on each component of the KGYM Architecture and then summarize the merits of KGYM.

Kbuilder: `Kbuilder` purely focuses on the task of compiling a kernel according to the user’s specifications. These specifications include (1) `git-url` - a URL to the git tree of the kernel, (2) `commit-id` - a specific git commit id, (3) `kernel-config` - the set of config values to use when compiling the codebase, (4) `user-img` - the userspace image to run the compiled kernel on (currently we give four options - `buildroot`, `debian-bullseye`, `debian-buster` and `debian-stretch`), (5) `compiler` - the choice of either `gcc` or `clang` to compile the kernel, (6) `linker` - the choice of either `ld` or `ld.llvm`

to link the modules, (7) *arch* - the architecture of the compiled kernel (currently we only support amd64) and (8) *patch* - an optional patch specified in a git diff format.

Using the above inputs, Kbuilder clones the git repository, performs a git checkout to the specified commit id, applies the patch if provided, compiles the kernel with *syz-build* using the compiler, linker and kernel config, places the kernel in the userspace image and finally uploads the entire disk-image to Google Cloud Storage. Note, as it takes a long time to even clone the Linux kernel (10 to 20 minutes), we optimize this step by caching Linux codebases from different git trees, thus allowing us to start the build process from the git checkout step.

Kreproducer: After compiling the Linux kernel and storing the disk image, we then execute the reproducer file using Kreproducer. As Syzkaller runs all of its fuzzing operations on GCE (google cloud engine) instances, we try to replicate this reproduction environment to maximize our chances of reproducing a bug. Hence, Kreproducer uses a pre-compiled disk image (either from Kbuilder or otherwise) to launch a GCE instance and runs a reproducer file that internally invokes a series of system calls on the kernel. Kreproducer then monitors and collects important information during the execution. If the reproducer file crashes the instance, Kreproducer will collect kernel panic information from the serial port output of the instance. However, if the reproducer file does not crash the kernel, the reproducer continues to run until the maximum time elapses (10 minutes by default). Hence using Kreproducer we can effectively determine if the bug has been resolved or if the bug persists.

Scheduler: One of the main reasons why KGYM is scalable is because of the architectural design of the scheduler. When a user submits a batch job containing hundreds of kernel compilations and executions, the scheduler inspects each job and delegates parts of each job to either the Kbuilder or Kreproducer. Additionally, as multiple Kbuilders/Kreproducers can be hosted on separate VMs, the scheduler can coordinate the execution of multiple jobs at a time. The scheduler keeps track of each job and its execution state in a lightweight SQLite3 database. We also provide an easy web UI that queries this database to provide real-time updates on each job.

Clerk: To make scheduling of jobs even easier, we offer *Clerk* - a client-side library that exposes many APIs for kernel building and reproducer file execution. Each API internally invokes the scheduler to run different kinds of jobs. Armed with KGYM and Clerk, code LLM researchers can now schedule kernel experiments with just a few lines of python code!

KGYM Workflow: We complete our explanation of KGYM with a dry-run of a representative kernel job. In this example, we assume that the kernel job involves both a kernel compilation and a reproducer file execution. As shown in Figure 5, we first issue this job using the Clerk library. The scheduler inspects the incoming job and notes two sequential and dependent steps - (a) building a kernel and (b) running a reproducer on the built kernel. To complete the first step, the scheduler issues a Kbuilder job using the message broker RabbitMQ (arrow ①). RabbitMQ then finds an available Kbuilder VM and issues this new job to the running Kbuilder (arrow ②). The Kbuilder accepts all the corresponding arguments, builds the kernel, and uploads the disk image to Google Cloud Storage. It then notifies the scheduler that the build process is completed by sending a message using a custom-built library called *messenger* (arrow ③ and arrow ④). Once the scheduler receives this message, it starts the second step by issuing a reproducer job (arrow ⑤) to RabbitMQ, which includes Kbuilder's output in the arguments. Like before, RabbitMQ finds an available Kreproducer VM and assigns this job to the running Kreproducer (arrow ⑥). Kreproducer consumes the corresponding arguments and runs the reproducer file on the kernel image. The reproducer runs until the kernel crashes or until the maximum allotted time. The job then finishes when Kreproducer communicates its results back to the scheduler (arrow ⑦ and arrow ⑧). Any KGYM user can easily monitor this multi-step process via our simple web UI interface.

Design Rationale: We arrived at this architectural design to make sure that KGYM is scalable and extensible. To scale KGYM, a user can simply increase the number of Kbuilder and Kreproducer VMs without changing any code implementation. Additionally, if a developer desires to extend KGYM, he/she can implement a new functionality (say KTask) and containerize it in a separate docker container. To exploit the benefits of KGYM, the developer can simply communicate with the scheduler (via rabbitMQ) using the *messenger* communication-library.

A.2 Bug Localization

Table 7: Bug Localization efficacy (complete overlap) of LLMs on Linux kernel bugs

	Model	GPT-4	GPT-3.5	Claude-3	Gemini-1.5	All Llama
	Top-N	Turbo	Turbo	Sonnet	Pro	Models
		(10)	(10)	(1)	(10)	(1)
Fix Type	Total Bugs	Oracle / BM25				
Single-Line	33	3 / 0	6 / 0	4 / 0	7 / 0	0 / 0
Single-Func	145	19 / 3	35 / 2	45 / 6	44 / 6	0-2 / 0-2
Multi-Func	57	0 / 0	7 / 0	2 / 0	2 / 0	0 / 0
Multi-File	44	0 / 0	3 / 0	1 / 0	1 / 0	0 / 0
Total	279	22 / 3	51 / 2	52 / 6	54 / 6	0-2 / 0-2

In addition to evaluating LLM-generated patches, we also study the bug localization ability of LLMs when given a kernel crash report. For this study, we perform a post-facto analysis of the generated patches from our crash resolution experiments in Table 6. For every `git diff` generated by an LLM, we extract all the modified functions and create a list of tuples of the form (function name, file name). These tuples are also extracted for every bug’s `Fix`. We then compute the overlap of both lists to measure the LLM’s ability to localize bugs.

Performance across models: In Table 7, for every queried LLM, we depict the number of bug patches (in the Oracle and BM25 settings) where the patch tuples are a superset of the `Fix` tuples. As seen, in the Oracle setting, the best results are achieved by Gemini-1.5 Pro closely followed by Claude-3 Sonnet and GPT-3.5 Turbo. It is important to note that despite only taking Top-1 from Claude-3 Sonnet, its bug localization performance is almost as good as a Top-10 output from Gemini-1.5 Pro. In the BM25 setting, both Claude-3 Sonnet, as well as Gemini-1.5 Pro, achieve a full overlap for 6 bugs. This low performance can be mainly attributed to the poor localization results of BM25.

For the open-source Llama models, bug localization is still a challenge with 2 being the best metric across all the Llama models in both settings.

Performance across Fix Types: When comparing the performance of models across `Fix` types, we notice that the best performance across models is in the Single Function category. This implies that for most models, the LLM-generated patches modify functions that overlap with the buggy function of the `Fix`. We also notice poor performance for the Multi-Function (but single file) and Multi-file categories. Hence, the LLMs struggle to include all the functions modified in the `Fix` when the developer-written fixes are complicated and spread out.

Table 8: Bug Localization efficacy (**partial** overlap) of LLMs on Linux kernel bugs

Model	GPT-4	GPT-3.5	Claude-3	Gemini-1.5	All Llama
Top-N	Turbo	Turbo	Sonnet	Pro	Models
	(10)	(10)	(1)	(10)	(1)
Oracle / BM25					
Partial Overlap	18 / 2	12 / 4	28 / 4	22 / 3	0-1 / 0
Overlap %	31.6 / 29.16	47.91 / 39.58	38.16 / 45.83	36.29 / 50	0-50 / 0

For completeness, in Table 8, we provide the number of patches that partially overlap with the actual `Fix`. Additionally, we also provide the overlap ratio (i.e., recall) to quantify the degree of overlap in these cases.

Overlap of Fix functions with crash report: It is important to quantify how much information LLMs can use from `Crashparent` to successfully localize the buggy functions modified in the `Fix`. For this, in Table 9, we depict the overlap of the functions mentioned in the crash report against those modified by the `Fix`. As shown, in both the BM25 and Oracle settings, less than 30% of the crash reports have textual references to all the functions modified in the `Fix` patch (i.e., less than

30% complete overlap). Additionally, in both settings, more than 50% of crash reports have no overlap with the functions modified in the Fix. This indicates that bug localization is indeed a very challenging problem in the Linux codebase. Given the absence of information in `Crashparent`, we believe that more information needs to be extracted from the dynamic traces of the execution to perform bug localization.

Table 9: Overlap between `Crashparent` and Fix

Setting	Complete Overlap	Partial Overlap	No Overlap	Total
BM25	75	45	155	275
Oracle	67	39	121	227

A.3 Prompt Template

Models are prompted with the template below during the crash resolution experiments.

You will be provided with a partial code base and an issue statement explaining a problem to resolve.

```
<issue>
{CRASH TEXT}
</issue>

<code>
[start of file_1]
{file_1 text}
[end of file_1]
[start of file_2]
{file_2 text}
[end of file_2]
...
</code>
```

Here is an example of a patch file. It consists of changes to the code base. It specifies the file names, the line numbers of each change, and the removed and added lines. A single patch file can contain changes to multiple files.

```
<patch>
--- a/file.py
+++ b/file.py
@@ -1,27 +1,35 @@
def euclidean(a, b):
- while b:
- a, b = b, a % b
- return a
+ if b == 0:
+ return a
+ return euclidean(b, a % b)

def bresenham(x0, y0, x1, y1):
points = []
dx = abs(x1 - x0)
dy = abs(y1 - y0)
- sx = 1 if x0 < x1 else -1
- sy = 1 if y0 < y1 else -1
- err = dx - dy
+ x, y = x0, y0
+ sx = -1 if x0 > x1 else 1
```

```

+ sy = -1 if y0 > y1 else 1
- while True:
- points.append((x0, y0))
- if x0 == x1 and y0 == y1:
- break
- e2 = 2 * err
- if e2 > -dy:
+ if dx > dy:
+ err = dx / 2.0
+ while x != x1:
+ points.append((x, y))
err -= dy
- x0 += sx
- if e2 < dx:
- err += dx
- y0 += sy
+ if err < 0:
+ y += sy
+ err += dx
+ x += sx
+ else:
+ err = dy / 2.0
+ while y != y1:
+ points.append((x, y))
+ err -= dx
+ if err < 0:
+ x += sx
+ err += dy
+ y += sy
+ points.append((x, y))
return points
</patch>

```

I need you to solve the provided issue by generating a single patch file that I can apply directly to this repository using git apply. Please respond with a single patch file in the format shown above. Respond below:

A.4 Subset of KBENCHSYZ for every model

Table 10: For each LLM, the final subset of bugs from the KBENCHSYZ depends on the chosen retrieval method and the maximum allowed context length.

All Bugs	Retrieval Method	Context Length	GPT-3.5 Turbo	GPT-4 Turbo	Claude-3 Sonnet	Gemini-1.5 Pro	Llama Models
279	BM25	16K	227	×	×	×	227
279	BM25	50K	×	275	275	275	×
279	Oracle	16K	117	×	×	×	117
279	Oracle	50K	×	228	228	228	×

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: We have extensively used KGYM and KBENCHSYZ proposed in the paper to conduct more than 30k kernel experiments.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: The paper states that we perform only baseline experiments on kernel crash resolution and admits that there exists much scope for additional research.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory Assumptions and Proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: There are no theoretical results mentioned in the paper.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental Result Reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer:[Yes]

Justification: Section 3 details the entire process of running KGYM’s end-to-end pipeline. For each bug in KBENCHSYZ, we provide in a JSON file all the necessary metadata to run the kernel experiment - such as the `Reproducer`, `Config`, `Commitparent` and `Crashparent`.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We plan to open-source the code for KGYM and openly release the KBENCHSYZ dataset.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental Setting/Details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: In our experiments, we only use a test set and do not perform any pre-training or fine-tuning as KBENCHSYZ is a low-resource dataset. We have provided a thorough analysis of the test set in Section 4.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment Statistical Significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [No]

Justification: We do not report error bars in our prompting experiments due to budget constraints. As the prompt for each bug in KBENCHSYZ runs into tens of thousands of tokens, repetitively querying state-of-the-art LLMs is prohibitively expensive.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.

- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments Compute Resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: We mention the number (and type) of VMs used when running KGYM for all the kernel experiments.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code Of Ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: We have followed all ethical guidelines.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader Impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [NA]

Justification: There is no societal impact of KGYM and KBENCHSYZ.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.

- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: The paper poses no such risks.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: The data used in KBENCHSYZ is directly scraped from the Syzkaller website. In the provided data dump, we only include specific HTML links to certain files hosted on the Syzkaller website and a script that uses these links to download all these files. Hence we do not violate any license terms. In our codebase, we also use and modify repositories having the MIT License. We have made sure to respect the terms of this License.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.

- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New Assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [Yes]

Justification: We open-source KGYM under the MIT License and provide detailed documentation along with it.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and Research with Human Subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.

- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.