

BIGCODEBENCH: BENCHMARKING CODE GENERATION WITH DIVERSE FUNCTION CALLS AND COMPLEX INSTRUCTIONS

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ABSTRACT

Task automation has been greatly empowered by the recent advances in Large Language Models (LLMs) via Python code, where the tasks ranging from software engineering development to general-purpose reasoning. While current benchmarks have shown that LLMs can solve tasks using programs like human developers, the majority of their evaluations are limited to short and self-contained algorithmic tasks or standalone function calls. Solving challenging and practical tasks requires the capability of utilizing *diverse function calls as tools* to efficiently implement functionalities like data analysis and web development. In addition, using multiple tools to solve a task needs compositional reasoning by accurately understanding *complex instructions*. Fulfilling both of these characteristics can pose a great challenge for LLMs. To assess how well LLMs can solve challenging and practical tasks via programs, we introduce BigCodeBench, a benchmark that challenges LLMs to invoke multiple function calls as tools from 139 libraries and 7 domains for 1,140 fine-grained tasks. To evaluate LLMs rigorously, each task encompasses 5.6 test cases with an average branch coverage of 99%. In addition, we propose a natural-language-oriented variant of BigCodeBench, BigCodeBench-Instruct, that automatically transforms the original docstrings into short instructions only with essential information. Our extensive evaluation of 60 LLMs shows that *LLMs are not yet capable of following complex instructions to use function calls precisely, with scores up to 60%, significantly lower than the human performance of 97%*. The results underscore the need for further advancements in this area.

The figure displays a programming task interface. On the left, a code editor shows the following Python code:

```
import http.client
import socket
import ssl

def task_func(server_name, server_port, path):
    """
    Makes an HTTPS GET request to a specified
    server and path, and retrieves the response.
    Parameters: ...
    Returns: ...
    Raises: ...
    Requirements: ...
    Examples: ...
    """
```

To the right of the code editor are several panels:

- Parameters:** Lists `server_name (str)`: Name of the server to which the request is made, `server_port (int)`: Port number of the server to which the request is made, and `path (str)`: Path to the HTTP request.
- Returns:** `str`: Response body from the server.
- Raises:** `ssl.SSLError`: on SSL handshake error.
- Requirements:** Lists `http.client`, `socket`, and `ssl`.
- Examples:** Shows a code snippet: `> res = task_func('ai.com', 443, '/v1')` and `> isinstance(res, str)` returning `True`.
- Test Case Class:** Shows a class with methods `setup()`, `teardown()`, `test_return_type(...)`, `test_different_paths(...)`, `test_connection_err_handling(...)`, `test_response_content(...)`, and `test_ssl_handshake_err_handling(...)`.

Figure 1: Programming tasks in BigCodeBench are structured with complex instructions in the docstrings, annotated by experts. The behavior of the solution is evaluated against a class of rigorous test cases with the proper environment setup.

1 INTRODUCTION

Task automation, including competitive programming (Li et al., 2022; Hendrycks et al., 2021; Jain et al., 2024), GitHub issue resolution (Yang et al.), and question answering (Gao et al., 2023; Chen et al.), has attracted significant interest from academia and industry to facilitate the development of advanced models for code, especially in Python (Wang et al.). With recent advances in data-centric

054 deep learning techniques, large language models (LLMs) trained on large-scale corpora have shown
 055 superior capabilities of translating textual inputs to syntactically correct and functional programs.
 056 However, widely-used benchmarks like HumanEval (Chen et al., 2021) and MBPP (Austin et al.,
 057 2021) only contain short, self-contained, and algorithm-focused programming tasks and have been
 058 saturated by recent model releases. In this work, we aim to close the evaluation gap between these
 059 isolated coding exercises and real-world programming, asking **Can LLMs solve more challenging**
 060 **and more practical tasks via programs?**

061 *Solving programming tasks* in real-world scenarios typically has two main characteristics: (1) **Diverse**
 062 **Function Calls as Tools**.¹ A complex programming task often requires the invocation of diverse
 063 function call sequences as tools (Robillard & DeLine, 2011; Hu et al., 2018; Qin et al., 2023). To
 064 avoid reinventing the wheel, domain-specific libraries are designed to cover function calls (or APIs)
 065 with comprehensive functionalities; and (2) **Complex Instructions**. Due to the complexity to perform
 066 various programming tasks, instructions may require compositional reasoning ability to perform a
 067 sequence of functionalities in the correct order (e.g., input data manipulation, error message handling,
 068 and specific output formatting) (Wiegiers & Beatty, 2013; Paetsch et al., 2003; Partsch, 2012). For
 069 instance, creating a network application that includes functionality for retrieving responses from an
 070 HTTPS server (Figure 1) requires integrating several components with multiple function calls, such
 071 as managing SSL contexts, handling socket connections, and ensuring the response is returned in the
 072 specific format.

073 Building a high-quality execution-based benchmark and the environment that simulates aforemen-
 074 tioned tasks with practical and challenging constraints is non-trivial. First, it is hard to naturally
 075 source self-contained programming tasks with complex instructions, unlike the short code exercises
 076 in HumanEval. Although most GitHub repositories contain realistic source code, the functions inside
 077 these repositories often require cross-file information (Ding et al., 2024). Second, real-world program-
 078 ming scenarios are extremely diverse (Zhout et al., 2023). Existing benchmarks (Zan et al., 2022b;
 079 Lai et al., 2023) only focus on popular scenarios like data science. Third, mainstream programming
 080 benchmarks have a significant number of ambiguous or under-specified specifications, resulting in
 081 inaccurate evaluation results (Siddiq et al., 2024; Jain et al.). While there have been attempts to
 082 improve the data quality with LLMs (Jain et al., 2023), LLMs have their own bias and cannot reliably
 083 perform refinement (Zheng et al., 2024a).

084 To construct massive high-quality programming tasks, we propose a novel framework (Figure 2) that
 085 uses collaboration between LLMs and human experts to build a rigorous execution-based benchmark,
 086 BigCodeBench. Particularly, we utilize LLMs to source programming tasks, refactor programs,
 087 and add test cases, under constant human supervision. Our benchmark contains 1,140 rich-context
 088 and multi-tool-use programming tasks in Python, covering 723 function calls from 139 popular
 089 libraries across 7 domains. As we aim to let models reason any suitable function calls to complete the
 090 tasks via code, we design the unit test cases in an open-ended manner and examine certain behaviors
 091 based on different inputs (Jain et al.). We assess two common programming scenarios: (1) Code
 092 Completion (BigCodeBench-Complete), which evaluates the capability of code generation
 093 based on the structured docstrings; and (2) Instruction to Code (BigCodeBench-Instruct),
 094 which evaluates the ability to complete programming tasks based on natural-language-oriented
 095 (NL-oriented) instructions. While BigCodeBench-Complete emphasizes structured docstring
 096 prompts, BigCodeBench-Instruct challenges LLMs to generate precise code without relying
 097 on non-essential details like [interactive Python examples](#).

098 Through extensive studies on 60 models, we find that LLMs still struggle to invoke multiple function
 099 calls from cross-domain libraries and follow complex instructions to solve programming tasks
 100 using Python. Specifically, the best performing LLM, GPT-4o, solves merely 60% of tasks on
 101 BigCodeBench-Complete and less than 50% on BigCodeBench-Instruct, indicating that
 102 LLMs themselves lack the ability to align with human expectations when instructions are more
 103 natural. Interestingly, we find that some instruction-tuned LLMs like GPT-4 constantly refuse to
 104 follow long instructions to repeat essential context and thus fail the test cases. Furthermore, LLMs
 105 perform differently when using domain-specific function calls as tools. We also demonstrate the

106 ¹In this work, we refer to “tools” as library-oriented but non-object-oriented Code Function Call APIs, which
 107 are discussed in [Gorilla OpenFunctions](#). The Code Function Calling APIs are typically seen in common
 external Python packages like Numpy, Sklearn, and Pandas.

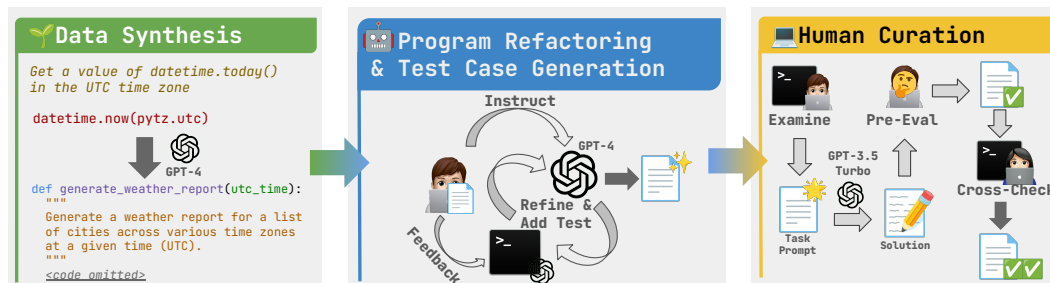


Figure 2: Each programming task in BigCodeBench is created through a three-stage construction process. The task quality is controlled by the human-LLM collaboration.

strongly positive correlations between mainstream benchmarks and BigCodeBench, validating our evaluation results.

2 BENCHMARK CONSTRUCTION

In this section, we introduce our human-LLM-collaboration framework for the BigCodeBench construction. As shown in Figure 2, the process of BigCodeBench-Complete encompasses three stages: Data Synthesis, Semi-automatic Program Refactoring and Testing Case Generation, and Human Curation. In addition, we construct BigCodeBench-Instruct in Section 2.4, an NL-oriented benchmark for programming-task solving. Further information is available in Appendix A and Appendix I. The construction is progressively contributed by 20 authors as annotators for one year in total, with 75% of them having more than 5 years of experience in Python programming. The progress is continually managed by the lead annotator to control the data quality. Each constructed programming task is expected to: (1) have clear instructions inside PEP-257-structured docstrings; (2) use multiple libraries as tools to solve the problem; and (3) be paired with at least five test cases encapsulated in the `unittest` framework, with a complex test setup (e.g., database connection, and directory creation), to verify program behaviors instead of relying on simple input-output assertions.

2.1 DATA SYNTHESIS

One intuitive method would be to rely on source code repositories to construct the function-level programming tasks. However, most repository-level functions require cross-file information, such as customized modules (Ding et al., 2024), which are hard to self-contain and document. We argue that leveraging LLMs to synthesize customized programming tasks can be more viable (Wei et al., 2023; Luo et al., 2023), especially when overseen by humans. Given a code snippet of API usage with a brief human instruction as the seed example (Figure 2), an LLM is instructed to enrich the programming intent and refine the corresponding implementation by using diverse libraries. Specifically, we use seed examples from ODEX (Wang et al., 2023c), a benchmark containing intent-paired code skeletons from Stack Overflow. We use the GPT-4 API², the strongest LLM at the time of data sourcing, to synthesize the programming tasks. To help the LLM synthesize self-contained and relevant programming tasks based on the seed example, we instruct the model with a 2-shot in-context demonstration (Appendix I.1) crafted by the lead annotator.

As previous studies have shown that LLMs favor their own generations (Zheng et al., 2024a; Panickssery et al., 2024), such phenomena can make the model evaluation unfair. We mitigate the model biases with an obfuscation and perturbation process. We first replace the semantic-rich program entry points with dummy function names. In addition, we perturb the natural language descriptions in docstrings with the back-translation method of NL-Augmenter (Dhole et al., 2023), inspired by ReCode (Wang et al., 2023a). After validating the post-processed programs with an abstract syntax tree parser, we collected 4,718 function-level programming samples.

²We use the model version `gpt-4-0613`.

2.2 SEMI-AUTOMATIC PROGRAM REFACTORING AND TESTING CASE GENERATION

Programs synthesized by LLMs may contain various issues, such as undeclared variables and runtime bugs. Without proper verification, the implementation cannot directly serve as a ground-truth solution. To construct a high-quality execution-based benchmark, we need to add test cases that can rigorously verify the correctness of programs and identify any bugs. However, it takes non-trivial effort for human developers to understand synthesized programs and properly refactor them with thorough testing. To improve the program quality and ease human annotation, we propose a conversion-driven framework for program refactoring and test case generations inspired by (Xia & Zhang, 2023). Specifically, we utilize the `Code Interpreter` session in the web-based GPT-4, which is back-ended by a Linux-based virtual environment with pre-installed Python packages. We engage 13 authors as human annotators (including the lead annotator) for this step, assigning each annotator 100 randomly sampled programming tasks based on their preferences of code topics (Appendix I.2.1). We detail the design of this human-in-the-loop framework from human and LLM aspects as follows:

Human Aspect Human developers possess varying preferences and levels of familiarity with specific data types and programming scenarios. To aid human annotators in providing more precise feedback for refining programs with GPT-4, we have defined 10 data types (e.g., SQL, CSV, and Python built-in types) and task scenarios (e.g., data analysis, networking, and visualization). GPT-4 API is utilized to automatically classify each program according to these categories, with detailed descriptions available in Appendix I.2.1. The annotators’ role is to continually instruct GPT-4 to `refactor` the programs and to provide continuous feedback to guide the model whenever it fails to self-debug or incorrectly refactor the program.

LLM Aspect To effectively guide GPT-4 in the iterative refinement of programs and test cases, we provide detailed annotation guidelines in Appendix I.2.2 as an initial prompt. These guidelines encompass two high-level instructions: (1) Refine the function, including its docstrings, to enhance realism and reduce ambiguity; and (2) Write unit tests to ensure the functional correctness of the given program description. Specifically, the model is taught to follow a step-by-step refinement process: (1) Remove unused libraries and add necessary libraries if they are missing in the code snippet; (2) Reformat docstrings to adhere to `PEP-257` conventions; (3) Align program implementations with the instructions inside docstrings; (4) Write and execute unit tests to ensure they pass; and (5) Add refined programs and test cases to files for downloading.

During interactions with GPT-4, we identify two main drawbacks in the `Code Interpreter` session. First, GPT-4 struggles to write proper test cases when mocking tests are employed. While the model can generate high-level designs of mocking tests, it often fails to understand how test cases should be constructed based on execution feedback. Second, GPT-4 can become stuck while resolving runtime bugs, leading to iterative refinement until the session times out. Continuous human feedback on viable solutions is essential to address these issues and ensure the model stays on track.

During the post-processing of the annotated data, we observe that a significant number of test cases were incomplete. This issue arises because GPT-4 often omits partial content when writing long contexts into files. After removing all invalid programs via program analysis, we end up with 1,223 refactored programming tasks with paired test cases.

2.3 HUMAN CURATION

To enhance the benchmark quality, we implement a three-fold human curation process:

Examination We first perform a rigorous manual examination of the benchmarks, guided by a set of detailed guidelines (Appendix I.3) to add more test cases and resolve a list of runtime issues due to the LLM-generated flaky tests (Luo et al., 2014). In addition, we aim to formalize further the programming tasks based on the following criteria: (1) The task should utilize at least two libraries to enrich the task scopes; (2) Import statements should be limited to those used in the task implementations and be natural based on human understanding; (3) The docstring should follow `PEP-257` to ensure consistent styles; (4) Both the task implementation and test cases should be clearly aligned with the task docstrings, based on human understanding; and (5) Required library modules in the docstrings should be aligned with the import statements. For test case construction,

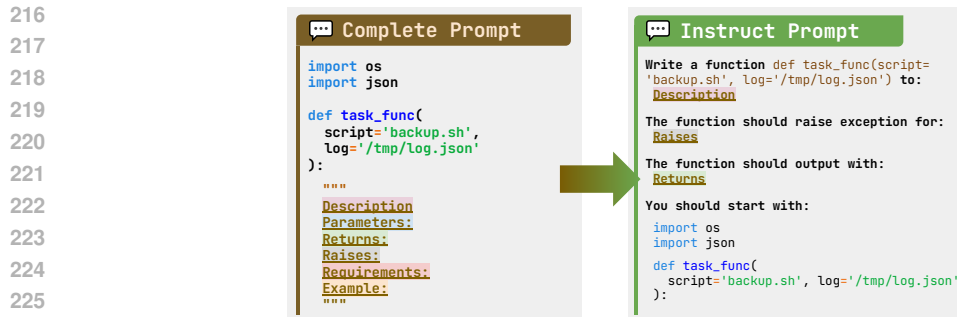


Figure 3: Each task prompt in BigCodeBench-Instruct are transformed from BigCodeBench-Complete via the pre-defined rules. We omit non-essential details during the transformation.

the criteria are as follows: (1) Test cases should be encapsulated by the `unittest` framework, making them `pytest`-compatible; and (2) Test cases need to be deterministic, asserting expected program behaviors based on the inputs (Jain et al.).

Pre-Evaluation To enhance the benchmark quality, we perform a dry run to pre-evaluate an LLM other than GPT-4 used in previous steps. We choose GPT-3.5-Turbo API³ to generate solutions based on the examined task prompts. By understanding how the model fails on the tasks, annotators may add essential details to the docstrings to clarify the task instructions but avoid describing step-by-step implementations.

Cross-Checking To further validate data quality and ensure consistency across all programming tasks in the testing environment, 7 additional annotators refine and finalize the data annotated by others. This round focuses on the utility of docstrings and test cases. We automatically parse the docstrings and ask annotators to manually correct the docstring structures, specifically addressing task descriptions, function parameters, expected returns, exception handling, required modules, and interactive examples. Additionally, we remove unused imported modules via program analysis. For the interactive examples, we ensure their correctness via `doctest`, except for those requiring system and network access. The confirmed programming tasks are finally validated by the automated test workflows in [GitHub Container Registry](#), where the test cases are automatically run against the task implementations in a configured sandbox environment. To ensure the finalized data quality, we randomly assign 33 finalized task prompts to the 11 annotators (the lead annotator was excluded; one annotator was unavailable at the time), to write the solutions. The lead annotator conducts the evaluation of the solutions, finding that 97% (32 out of 33) of sampled tasks can pass all test cases.

2.4 BENCHMARKING NL-ORIENTED INSTRUCTIONS TO CODE GENERATION

When instruction tuning LLMs using NL data, the input is mainly an NL instruction, and the target output is the NL or source code for completion (Muennighoff et al., 2023). This training objective aligns with the downstream applications such as multi-turn dialogue, where users ask questions or provide task-specific instructions to the models. While existing programming benchmarks commonly format the verbose instructions in docstrings (Chen et al., 2021), users may instruct the models to generate code samples with the less verbose NL context. Despite that there have been similar attempts like HumanEvalPack (Muennighoff et al., 2023) addressing this limitation, their inputs still lack some naturalness. Generally, users tend to describe the high-level idea of functionalities and avoid redundant information (e.g., parameters) or too-specific details (e.g., interactive examples). Thus, we create BigCodeBench-Instruct, a benchmark variant that prompts LLMs to solve programming tasks with more NL-oriented instructions, assessing the model’s ability to understand human requirements correctly. Based on the task prompts created in BigCodeBench-Complete, we design a set of parsing rules and transform them into more natural instructions (Figure 3). For quality control, 5 authors who do not participate in previous stages inspect the randomly sampled

³We use model version `gpt-3.5-turbo-1106`.

prompts and their corresponding ground-truth solutions and reach an agreement on the alignment between the instruction prompts and task implementations.

3 BENCHMARK STATISTICS








Domain	Library	Function Call
Computation (63%) 	pandas, numpy, sklearn, scipy, math, nltk, statistics, cv2, statsmodels, tensorflow, sympy, textblob, skimage...	pandas.DataFrame, numpy.random, numpy.random.seed, numpy.array, numpy.mean, pandas.read_csv, numpy.random.randint, pandas.Series...
General (44%) 	random, re, collections, itertools, string, operator, heapq, ast, functools, regex, bisect, inspect, unicodedata...	collections.Counter, random.seed, random.randint, random.choice, re.sub, re.findall, itertools.chain...
Visualization (31%) 	matplotlib, seaborn, PIL, folium, wordcloud, turtle, mpl_toolkits	matplotlib.pyplot, matplotlib.pyplot.subplots, matplotlib.pyplot.figure...
System (30%) 	os, json, csv, shutil, glob, subprocess, pathlib, sqlite3, io, zipfile, sys, logging, pickle, struct, psutil...	os.path, os.path.join, os.path.exists, os.makedirs, glob.glob, os.listdir, json.load, csv.writer, shutil.move...
Time (10%) 	datetime, time, pytz, dateutil, holidays, calendar	datetime.datetime, datetime.datetime.now, time.time, time.sleep, datetime.datetime.strptime...
Network (8%) 	requests, urllib, bs4, socket, django, flask, ipaddress, smtplib, http, flask_mail, cgi, ssl, email, mechanize...	arse.urlparse, django.http.HttpResponse, ipaddress.IPv4Network, smtplib.SMTP, requests.post, socket.gaierror...
Cryptography (5%) 	hashlib, base64, binascii, codecs, rsa, cryptography, hmac, blake3, secrets, Crypto	cryptography.fernet.Fernet.generate_key, cryptography.hazmat.primitives.padding, cryptography.hazmat.primitives.padding.PKCS7...

Figure 4: Examples of tools in BigCodeBench are illustrated. Each function call belongs to a domain-specific library. The distribution of each domain is computed based on the frequency of domain-specific libraries appearing per task. For example, “63%” in “Computation” means that there are 63% tasks in BigCodeBench using at least one computation library.

Table 1: Summarized statistics of representative function-level Python programming benchmarks, partially inspired by (Zan et al., 2023). BigCodeBench are more complex regarding the depth of task complexity and breadth of tool-use knowledge. **Cov.:** Branch Coverage. **Char.:** Characters. **C.C.:** Cyclomatic Complexity (starting from 0, higher values indicate more complex code). **Lib.:** Library. **Dom.:** Domain. **Std.:** Python Standard Library. **Ext.:** Python External Library.

Overall Statistics								
Benchmark	# Task	Test (Avg.)		Prompt (Avg.)		Solution (Avg.)		
		#	Cov.	Char. (Code)	Line	Char.	Line	C.C.
HumanEval	164	7.8	98%	450.6 (450.6)	13.7	180.9	6.8	3.6
DS-1000	1,000	1.6	98%	871.8 (193.9)	29.1	138.1	5.1	1.6
DS-1000 (Orig.)	452	1.5	98%	831.4 (201.2)	26.2	115.5	4.2	1.4
ODEX	945	1.8	96%	87.5 (87.5)	1.0	50.4	1.9	1.4
BigCodeBench-Complete	1,140	5.6	99%	1112.5 (1112.5)	33.5	426.0	10.0	3.1
BigCodeBench-Instruct				663.2 (124.0)	11.7			
Tool Statistics								
Benchmark	# Dom.	# Lib.	# Call	Tasks (Avg.)		Combination		
		Std. / Ext.	Std. / Ext.	# Lib.	# Call	# Lib.	# Calls	# Dom.
HumanEval (Chen et al., 2021)	3	4 / 0	7 / 0	0.1	0.1	6	8	5
DS-1000 (Lai et al., 2023)	4	5 / 9	7 / 321	0.8	1.1	66	331	24
DS-1000 (Orig.) (Lai et al., 2023)	4	4 / 9	5 / 289	0.9	1.3	59	260	23
ODEX (Wang et al., 2023c)	7	40 / 26	128 / 102	0.6	0.5	105	202	20
BigCodeBench	7	77 / 62	281 / 442	2.8	4.7	577	1045	56

Overall Statistics The first part of Table 1 presents an overview comparison between BigCodeBench and other mainstream function-level Python programming benchmarks. We note that the full DS-1000 dataset emphasizes the perturbed tasks to avoid model memorization and thus includes an original subset for reference. Therefore, we also include statistics for non-perturbed problems (DS-1000 Orig.). As the provided statistics suggest, BigCodeBench contains much more

rigorous execution-based evaluation and has longer task prompts that contain complex instructions. The ground-truth solutions are also longer than in prior benchmarks, indicating that the tasks inside BigCodeBench require more complex implementation logic. To illustrate the programming complexity, we measure cyclomatic complexity, which is the number of independent paths through the task solution. We notice that BigCodeBench has a similar complexity to HumanEval, much higher than DS-1000 and ODEX. The high cyclomatic complexity indicates that solving the tasks in BigCodeBench requires non-trivial reasoning ability from the programming perspective.

Tool Statistics In this work, we highlight any libraries and function calls from these libraries as program-based tools for LLMs (Qin et al., 2023). Therefore, we compare the tools used among the mainstream benchmarks in the second part of Table 1. First, BigCodeBench covers 281 function calls from 77 standard libraries and 442 from 62 external libraries, which is far more diverse than the other benchmarks. The examples of these tools are shown in Figure 4. Based on the PyPI download statistics, the mean download counts of the recent 30 days are 56.9M+ for the 62 external libraries, suggesting their high popularity in real-world software development. Second, BigCodeBench frequently invokes a sequence of function calls from multiple libraries to solve a single task, requiring significant compositional reasoning ability for task-solving. Third, BigCodeBench has more diverse combinations among libraries, function calls, and domains in the ground-truth solutions. We visualize the library and function call density used by different benchmarks in Appendix H, showing the even broader tool-use diversity in BigCodeBench. To better understand solution complexity (measured by characters) and tool-use diversity (measured by distinct function calls), we compare the tasks in BigCodeBench with those in representative benchmarks in Figure 5 (details are provided in Appendix H.2). We find that BigCodeBench requires more complex reasoning and problem-solving skills to implement comprehensive functionalities.

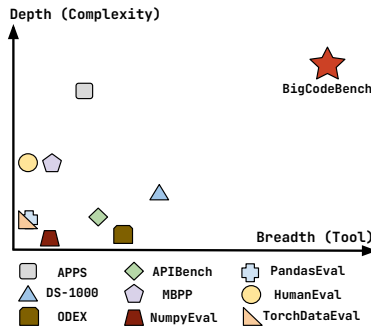


Figure 5: Complexity - tool comparisons with various benchmarks.

4 EVALUATION

Our evaluation uses the unbiased version of Pass@ K (Chen et al., 2021) to accurately assess the functional correctness of generated code snippets by LLMs. To make general observations, we extensively evaluate 60 state-of-the-art LLMs on BigCodeBench-Complete and 35 instruction-tuned LLMs on BigCodeBench-Instruct. Specifically, following prior works (Roziere et al., 2023; Liu et al., 2024; Lai et al., 2023), we report Pass@1 with greedy decoding for the main experiments in the zero-shot setting. To investigate more thoroughly, we compute Pass@1 and Pass@5 results with random sampling to generate N ($N=5$) samples with a temperature of 0.8 and top-p of 0.95 in Appendix K. While it is encouraged to generate much more ($N \geq K$) samples to avoid bias, we take the lower bound due to limited computational resources. We use the same prompts for code generation from (Liu et al., 2024), given in Appendix J.

4.1 MEASURING TASK-LEVEL PERFORMANCE

We first evaluate the task-solving performance of each LLM and summarize the findings as follows. We show the main results in Figure 6. As models constantly omit the essential code in the generation and hence fail the tests, we calibrate the generation quality by adding the missing setup and calculate Pass@1, which is denoted as calibrated Pass@1. The Pearson’s r correlation between the model ranks on BigCodeBench-Complete and BigCodeBench-Instruct is 0.982, indicating a strong alignment. In addition, model rankings show the signs of scaling laws (Kaplan et al., 2020), where bigger models can solve more tasks. We also observe that there is still some performance gap between the top closed models and open ones. Detailed studies can be found in Appendix L. We highlight a few findings as follows:

Instruction-tuned LLMs omit essential details of long code prompts Interestingly, we observe that instruction-tuned LLMs can omit the essential import statements of the given prompts

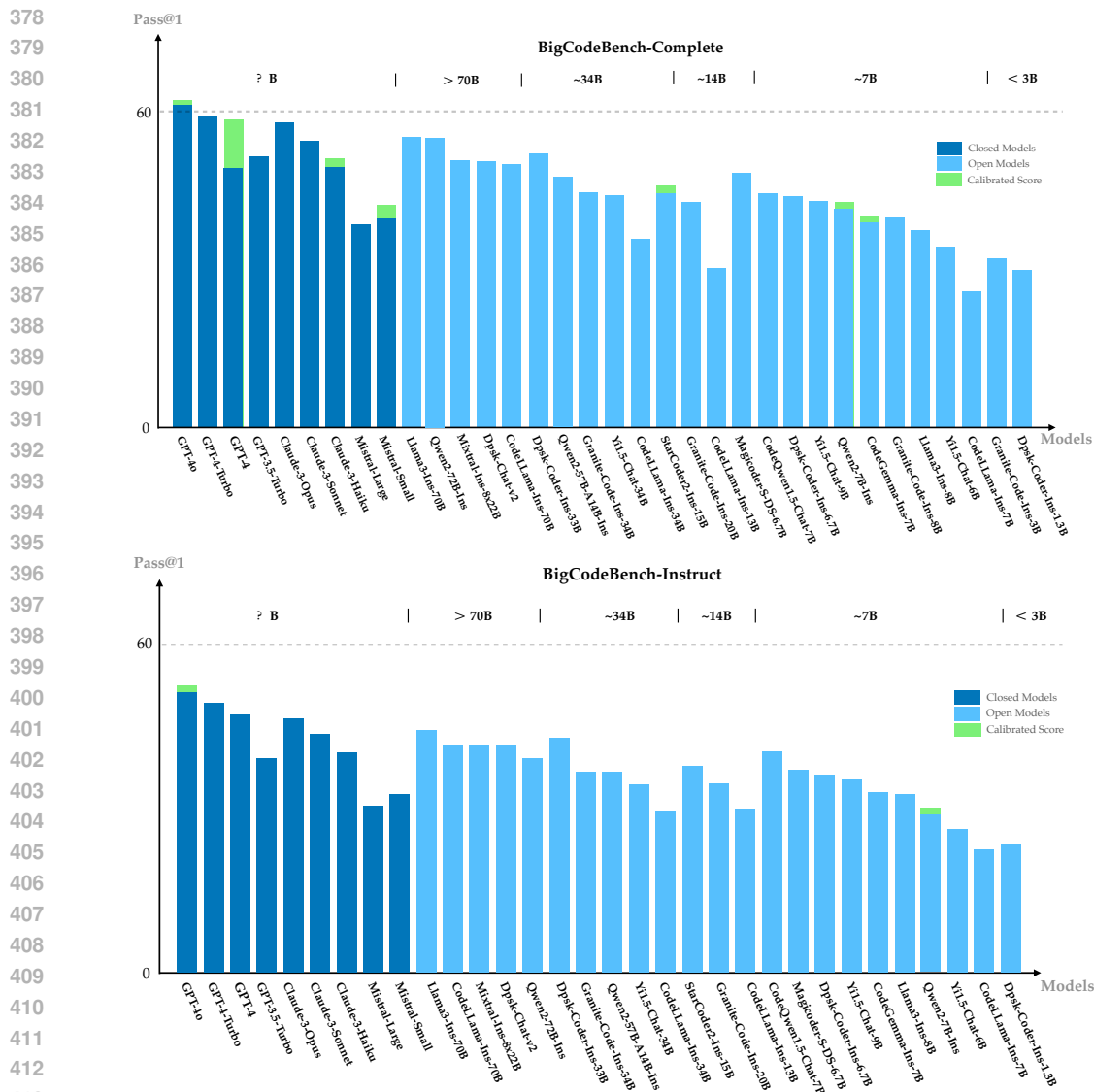


Figure 6: Pass@1 results of instruction-tuned LLMs on BigCodeBench-Complete (Top) and BigCodeBench-Instruct (Bottom). We only highlight the calibrated results having at least a difference of 1% from the original Pass@1.

in BigCodeBench-Complete, which can lead to task failure due to the lack of proper module and constant definitions. The omission is likely to happen when models need to repeat the long context in the response. Such behaviors are denoted as “model laziness” in long-context interactions, similar to the observations in Section 2.2. Due to the limited prompt length of existing programming benchmarks (Table 1), there is no quantitative evidence of the laziness phenomenon in prior code generation benchmarks. To understand how laziness can affect the model performance, we calibrate the generation quality by adding the missing setup (e.g., import statements and global constants). When comparing the calibrated Pass@1 and the original ones in the top figure of Figure 6 and Appendix K, we find that GPT-4 tends to omit much more context and perform poorly on BigCodeBench-Complete, consistent with the previous community discussion⁴ and confirmed by OpenAI (OpenAI, 2024b). While instruction-tuned LLMs have an average performance degradation of 0.8% on BigCodeBench-Complete, there is a less than 0.3% difference on BigCodeBench-Instruct, which validates the hypothesis that models omit more information of longer inputs.

⁴<https://community.openai.com/t/why-i-think-gpt-is-now-lazy>

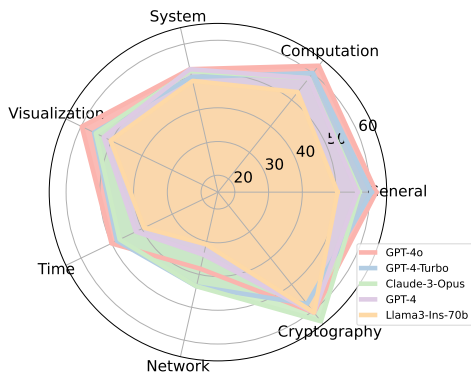
432 **Instruction tuning helps to follow programming constraints** When comparing instruction-
 433 tuned LLMs with their base ones (Appendix K), we observe that instruction tuning can improve
 434 the capability of following complex constraints of the prompts. The mean calibrated Pass@1 on
 435 BigCodeBench-Complete for instruction-tuned LLMs and paired base LLMs are 40.7% and
 436 35.7%, respectively, indicating the great performance gap. The performance disparity is further
 437 magnified when the instruction-tuned LLMs are calibrated. We also note that the task performance of
 438 CodeQwen1.5-7B is not enhanced by instruction tuning, possibly due to the lack of fine-grained data
 439 during training.

440 **LLMs are sensitive to the verbosity of programming instructions** From the bottom figure
 441 of Figure 6, we notice that LLMs perform much worse on BigCodeBench-Instruct than
 442 BigCodeBench-Complete with an average decrease of 8.5% on Pass@1, while maintaining
 443 similar rankings. This observation indicates that LLMs still lack the proper understanding of
 444 condensed human requirements since the task instructions of BigCodeBench-Instruct are
 445 less verbose. While it is possible that the lower verbosity may introduce more ambiguity, we
 446 make sure that the instructions transformed from BigCodeBench-Complete do not lose the
 447 key information from the human perspective. In addition, we find that models with lower scores
 448 on BigCodeBench-Complete degrade less on BigCodeBench-Instruct, limited by their
 449 programming capability.

451 4.2 MEASURING TOOL-LEVEL PERFORMANCE

452 Besides evaluating task completion performance, we
 453 try to understand how well LLMs can use tools for
 454 task-solving. As it is hard to evaluate the accuracy
 455 of each independent function call regardless of the
 456 correctness of the model solutions, we rely on the calibrated greedy decoding results on BigCodeBench-Complete and deem the use of the associated library correct if the task is passed by all test cases.

461 **Jack of all trades, master of most.** Figure 7 shows
 462 the top 5 calibrated instruction-tuned LLMs ranked
 463 on BigCodeBench-Complete. The best overall
 464 performing LLMs, like GPT-4o, excel in most domains but still fall short in certain ones. We suggest
 465 that domain specialization can result from the training data. Similar findings can be found in the base
 466 models, which are visualized in Appendix K.2.



467 Figure 7: Top 5 instruction-tuned LLMs on BigCodeBench-Complete.

469 Table 2: Tool-use comparisons between all generated solutions (Sol.) and ground truths (GT.) on BigCodeBench-Complete.

	Library (%)		Function Call (%)	
	<i>Sol.</i> \subseteq <i>GT.</i>	<i>Sol.</i> $\not\subseteq$ <i>GT.</i>	<i>Sol.</i> \subseteq <i>GT.</i>	<i>Sol.</i> $\not\subseteq$ <i>GT.</i>
Pass	79.84	20.16	40.46	59.54
Fail	71.78	28.22	22.47	77.53

476 **LLMs use different function calls to solve tasks.**

477 We assess how all 60 calibrated models use tools on BigCodeBench-Complete and report the
 478 mean statistics in Table 2. By inspecting the library usage, we find that models use imported libraries
 479 in more than 70% of tasks. For the remaining 20%, we notice that models tend to import additional
 480 libraries to solve the tasks. After some inspection, we notice that most of these added libraries
 481 are standard, explaining why they can still pass the tests. When analyzing the function calls, we
 482 find that models tend to use different function calls from the ones in ground truths. Due to the
 483 open-endedness of the programming tasks, the invocation of function calls is expected to be flexible.
 484 However, using more diverse function calls is more likely to introduce task failures. We provide
 485 several examples where the model-generated solution contains function calls different from the
 ground truth in Appendix L, Examples 9 and 10.

5 COMPARISON TO EXISTING PROGRAMMING BENCHMARKS

Table 3: Correlation coefficients measured by Pearson’s r and Spearman’s p . against HumanEval+ and LiveCodeBench.

	BigCodeBench-Complete		BigCodeBench-Instruct	
	r	p	r	p
HumanEval+	0.849	0.861	0.864	0.894
LiveCodeBench	0.853	0.898	0.778	0.815

We compare model performances on BigCodeBench-Complete against existing benchmarks like HumanEval+ (Liu et al., 2024) and LiveCodeBench (Jain et al., 2024) used for evaluating the coding capabilities of LLMs. We compute the Pearson and Spearman correlation coefficients for the calibrated model ranks on BigCodeBench-Complete and BigCodeBench-Instruct against HumanEval+ and LiveCodeBench. From Table 3, we observe the strong correlations for both coefficients, suggesting that BigCodeBench is well aligned with the mainstream evaluation trend. However, as BigCodeBench measures the different aspects from HumanEval+ and LiveCodeBench, some models are expected to have various ranks among these benchmarks. In addition, we note that models which have saturated HumanEval like GPT-4o, still have room for improvement on BigCodeBench in comparison to human performance. We also provide the analysis of other benchmarks in Appendix N.

6 RELATED WORK

Large Language Models for Code With the rise of LLMs, there have been various models trained on code. Codex (Chen et al., 2021) marks the first base LLM pre-trained on code, which was used as the backbone model for GitHub Copilot. More recently, pre-trained base code models (Nijkamp et al., 2022; Li et al., 2023; Lozhkov et al., 2024; Roziere et al., 2023) have been built to perform accurate code completion. Later, with the advance in instruction tuning (Ouyang et al., 2022), LLMs can generate the code snippet that aligns with the given NL instruction. Instruction-tuned code models (Muennighoff et al., 2023; Luo et al., 2023; Wei et al., 2023), are generally better at programming than their base ones.

Programming Benchmarks To assess the programming capability of LLMs, researchers have proposed many programming benchmarks. Most existing benchmarks focus on short, self-contained, and algorithm-specific programming tasks, such as HumanEval (Chen et al., 2021) and MBPP (Austin et al., 2021). Recently, open-domain coding benchmarks (Wang et al., 2023c; Lai et al., 2023) have been built to challenge code LLMs on application-specific scenarios by using specific sets of tools and libraries. However, they focus on simple intents and use limited specific function calls per programming task, making their evaluation less challenging and realistic. Benchmarks like SWE-bench (Jimenez et al., 2023) are built to evaluate the performance of a code agent framework (e.g., iterated prompting, real-time environment interaction, and long-context exploration). Our BigCodeBench focuses on evaluating the fundamental code generation capability of LLMs, which is also an essential path toward strong code agents. In addition, SWE-Bench is constructed from GitHub repositories with existing test cases — which limits the diversity of the tasks considered. In contrast, our collaborative LLM-human annotator procedure allows generating tasks from seed queries collected from (Wang et al., 2023c), tackling a broader range of software tasks.

7 CONCLUSION

We introduce BigCodeBench, a new high-quality programming benchmark constructed via the collaboration between human experts and LLMs, assessing the capability of tool use and complex instruction following. Through the extensive evaluation of 60 LLMs, we find that there is a long way for models to achieve perfection on this benchmark and share a few findings that can potentially improve the performance. We urge the community to work on more advanced LLMs for code and continually build upon our benchmark and extended BigCodeBench-Hard (Appendix E), as discussed in our long-term roadmap (Appendix F).

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APPENDIX

Contents

918		
919		
920		
921		
922		
923		
924		
925		
926	A Datacard	19
927		
928	B Data Sheet	20
929	B.1 Motivation	20
930	B.2 Composition/Collection Process/Preprocessing/Cleaning/Labeling and Use	20
931	B.3 Distribution	20
932	B.4 Maintenance	21
933		
934		
935	C Data Contamination	21
936		
937	D Extended Related Work	21
938		
939	E BigCodeBench-Hard	22
940		
941		
942	F Long-Term Roadmap and Call for Contributions	25
943	F.1 Limitations	26
944	F.2 BigCodeBench-OOD	27
945	F.3 BigCodeBench-Interact	27
946	F.4 BigCodeBench-Evolved	27
947		
948	G Artifacts	28
949		
950		
951	H Tool Statistics	30
952	H.1 Analysis	30
953	H.2 Comparison to Existing Programming Benchmarks	30
954	H.3 Version Control	31
955	H.4 Domain Classification	31
956		
957		
958	I Detailed Benchmark Construction	33
959	I.1 Data Synthesis Prompt	33
960	I.2 Semi-automatic Program Refactoring and Testing Case Generation	35
961	I.3 Human Curation Guidelines	37
962		
963	J Evaluation Setup	40
964	J.1 Inference	40
965	J.2 Execution	40
966	J.3 Prompt Template	40
967		
968		
969	K Detailed Benchmarking Results and Analysis	42
970	K.1 Detailed Results	42
971	K.2 Further Analysis	44

972	K.3 Prompting Techniques	44
973		
974	L Qualitative Studies	45
975		
976	M Unit Test Design	51
977		
978	N Comparison to More Programming Benchmarks	53
979		
980	O Evaluation on Less-Structured Instructions	53
981		
982	P bigcodebench: Evaluation Infrastructure	54
983		
984	Q Development Timeline	54
985		
986		
987		

A DATACARD

We follow (Bender & Friedman, 2018) to create the datacard for BigCodeBench, where we tend to summarize and centralize all information that might be relevant for the benchmark analysis.

Curation Rationale This is detailed in [Section 2](#) and [Appendix I](#).

Language Variety Information about our annotators’ nationality will not be provided, as the constructed benchmark is hardly related to regional or social dialects. However, we confirm that all communications during the annotation process are in mainstream English (en-US). We note that the first language of some annotators is not English, which can introduce some inaccurate expressions to the task prompts in BigCodeBench.

Curators Demographic The benchmark construction requires the great annotation effort of Curators, who are involved in the process detailed in [Section 2](#). They come from the following population:

- **Age:**
 - 18-25: 25% (5/20)
 - 26-35: 70% (14/20)
 - 36-45: 5% (1/20)
- **Experience in Python Programming (Years):**
 - 1-3: 5% (1/20)
 - 3-5: 20% (4/20)
 - 5+: 75% (15/20)
- **Academic Background:**
 - Bachelor: 5% (1/20)
 - Master: 20% (4/20)
 - PhD: 75% (15/20)

Text Characteristics This is detailed in [Section 3](#).

1026 **B DATA SHEET**

1027

1028 Besides the provided Databcard, we follow the documentation frameworks provided by (Gebru et al.,
1029 2021).

1030

1031 **B.1 MOTIVATION**

1032

1033 **B.1.1 FOR WHAT PURPOSE WAS THE DATASET CREATED?**

1034

1035 Our dataset aims at providing a thorough assessment of the capability of solving programming
1036 tasks. Particularly, we focus on the challenges and practicability of the tasks, and pinpoint two
1037 main characteristics that few benchmarks highlight: (1) Diverse Function Calling; and (2) Complex
1038 Instruction Following. This dataset will help stakeholders better understand the fundamental abilities
1039 and limitations associated with deploying LLMs.

1040 We believe that there are three main expectations of a good execution-based programming benchmark:

1041

- 1042 • The benchmark should be easy to use and efficient in evaluating the fundamental capabilities
1043 of LLMs. Repository-level benchmarks (e.g., SWE-bench (Yang et al.)) are not suitable for
1044 this purpose.
- 1045 • The benchmark should be practical, covering various programming scenarios. Algorithm-
1046 specific benchmarks (e.g., HumanEval (Chen et al., 2021) and MBPP (Austin et al., 2021))
1047 are unsuitable. Domain-specific benchmarks (e.g., DS-1000 (Lai et al., 2023)) are also
1048 unsuitable for this purpose.
- 1049 • The benchmark should be challenging, where the tasks require LLMs’ strong compositional
1050 reasoning capabilities and instruction-following capabilities. The benchmarks with simple
1051 tasks (e.g., ODEX (Wang et al., 2023c)) are unsuitable.

1052

1053 BigCodeBench is the first benchmark that meets all three expectations. It is an easy-to-use
1054 benchmark that evaluates LLMs with practical and challenging programming tasks, accompanied by
1055 an end-to-end evaluation framework BigCodeBench. We aim to assess how well LLMs can solve
1056 programming tasks in an open-ended setting.

1057

1058 **B.2 COMPOSITION/COLLECTION PROCESS/PREPROCESSING/CLEANING/LABELING AND USE**

1059

1060 The answers are described in our paper as well as the GitHub repository: **REDACTED**.

1061

1062 **B.3 DISTRIBUTION**

1063

1064 **B.3.1 WILL THE DATASET BE DISTRIBUTED TO THIRD PARTIES OUTSIDE OF THE ENTITY
1065 (E.G., COMPANY, INSTITUTION, ORGANIZATION) ON BEHALF OF WHICH THE DATASET
1066 WAS CREATED?**

1067

1068 No. Our dataset will be managed and maintained by the **REDACTED** community.

1069

1070 **B.3.2 HOW WILL THE DATASET BE DISTRIBUTED (E.G., TARBALL ON WEBSITE, API,
1071 GITHUB)?**

1072

1073 The evaluation dataset will be released to the public, and hosted on Hugging Face.

1074

1075 **B.3.3 WHEN WILL THE DATASET BE DISTRIBUTED?**

1076

1077 It has been released now.

1078

1079 **B.3.4 WILL THE DATASET BE DISTRIBUTED UNDER A COPYRIGHT OR OTHER INTELLECTUAL
1080 PROPERTY (IP) LICENSE, AND/OR UNDER APPLICABLE TERMS OF USE (TOU)?**

1081

1082 Our dataset is distributed under the Apache-2.0 license.

1080 B.4 MAINTENANCE

1081
1082 B.4.1 HOW CAN THE OWNER/CURATOR/MANAGER OF THE DATASET BE CONTACTED (E.G.,
1083 EMAIL ADDRESS)?1084 Please contact **REDACTED** and the **REDACTED** Project, who are responsible for maintenance.
10851086 B.4.2 WILL THE DATASET BE UPDATED (E.G., TO CORRECT LABELING ERRORS, ADD NEW
1087 INSTANCES, DELETE INSTANCES)?1088
1089 Yes. If we include more tasks or find any errors, we will correct the dataset hosted on Hugging Face
1090 and update the results in the leaderboard accordingly. It will be updated on our website.1091
1092 B.4.3 IF OTHERS WANT TO EXTEND/AUGMENT/BUILD ON/CONTRIBUTE TO THE DATASET, IS
1093 THERE A MECHANISM FOR THEM TO DO SO?1094 For dataset contributions and evaluation modifications, the most efficient way to reach us is via
1095 GitHub pull requests. For more questions, contact **REDACTED** and the **REDACTED** Project, who
1096 are responsible for maintenance.
1097

1098 C DATA CONTAMINATION

1099
1100 While `BigCodeBench` tasks are constructed from scratch, there are still some concerns regarding the
1101 potential data contamination. Therefore, we conduct N-gram contamination experiments on ODEX
1102 intents (English) and an anonymized archive of Stack Overflow used by StarCoder2 (Lozhkov et al.,
1103 2024), which may be correlated to `BigCodeBench` instructions. We also evaluated StarCoderData
1104 (Python) (Li et al., 2023), which has been widely used as the code training data for various LLMs. We
1105 focus on the overlaps between the `BigCodeBench` instructions and the queries contained by these
1106 data sources, using 10-gram and 13-gram setups (Brown, 2020; Elazar et al., 2023; Shao et al., 2024;
1107 Guo et al., 2024; Bai et al., 2023) to indicate potential data contamination. Due to the significant
1108 computational resources required, the 10-gram overlap on StarCoderData is timeout and thus omitted.
1109

1110 Table 4: Comparison of N-Gram data across different datasets.

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N-Gram	Overlap Percentage (%)		
	ODEX	Stack Overflow	StarCoderData
13	0.00	0.18	—
10	0.09	1.49	2.49

1117 As shown in Table 4, the likelihood of our task descriptions being contaminated by existing data is
1118 extremely low. With a stricter 10-gram configuration, no more than 2.5% of `BigCodeBench` tasks
1119 overlapped with the tested data sources.1120 In addition, we have carefully considered potential future data contamination issues before releasing
1121 `BigCodeBench`. To mitigate this, we have decided to release the data on Hugging Face rather than
1122 directly on GitHub. Based on past experiences, most contamination stems from the unintentional
1123 inclusion of GitHub source code, as seen with datasets like HumanEval and MBPP. Unlike GitHub,
1124 Hugging Face does not support the kind of automated scraping that typically leads to contamination,
1125 making `BigCodeBench` relatively safer from this issue. That said, we acknowledge that it is impossible
1126 to ensure complete privacy of benchmark data. For instance, when closed-source model APIs are
1127 used for inference, companies may collect and use the data for training if it is deemed high-quality.
1128 Preventing this would require access to their model weights and the ability to run them locally, which
1129 is not feasible in most cases.

1130 D EXTENDED RELATED WORK

1131
1132 **Large Language Models for Code** With the rise of LLMs, various models have been trained on
1133 code. The first series of models, like CodeBERT (Feng et al., 2020) and GraphCodeBERT (Guo

et al.), are built based on the BERT (Kenton & Toutanova, 2019) encode-only architecture, which specializes in code-understanding tasks such as defect detection and clone detection (Lu et al.). As there is an increasing need for automated code completion, the T5-based encoder-decoder architecture has been applied to train code-specific models like PyMT5 (Clement et al., 2020), PLBART (Ahmad et al., 2021), CodeT5 (Wang et al., 2021), CodeT5+ (Wang et al., 2023b), and GrammarT5 (Zhu et al., 2024). While these models are better at generating code and comments, they are not fully optimized. More LLMs for code have become decoder-only, following the design of GPT (Radford, 2018). The early decoder-only LLMs for code, trained with left-to-right token prediction, cannot assist developers in inserting code between programs. To fulfill this need, InCoder (Radford, 2018) has been designed to allow code infilling. Subsequently, the combination of left-to-right and fill-in-the-middle code generation has been widely adopted in later model development, such as StarCoder (Li et al., 2023), CodeLlama (Roziere et al., 2023), and DeepSeek-Coder (Guo et al., 2024). However, these models are pre-trained only and are denoted as base models. With advances in instruction tuning (Ouyang et al., 2022), more LLMs for code are further fine-tuned on natural language instructions to better understand user queries. For example, WizardCoder (Luo et al.) and MagiCoder (Wei et al., 2024) are instruction-tuned with synthetic data containing diverse instruction-code pairs. Later, OpenCodeInterpreter (Zheng et al., 2024b) developed a multi-turn instruction dataset and achieved better coding performance. More recently, there has been a growing interest in agentic programming (Yang et al.), developing prompting systems to enhance the capabilities of performing software engineering tasks, like GitHub issue resolution and code search. However, they are agnostic regarding the backbone models. In this work, we aim to assess the fundamental capabilities of LLMs in practical code generation without any customized prompting systems.

Programming Benchmarks To assess the programming capability of LLMs, researchers have proposed various programming benchmarks. Most existing benchmarks focus on short, self-contained, algorithm-specific programming tasks, such as HumanEval (Chen et al., 2021) and MBPP (Hendrycks et al., 2021). While there are other programming benchmarks like APPS (Hendrycks et al., 2021) and CodeContests (Li et al., 2022), they are not frequently used due to the lack of an easy-to-use evaluation infrastructure. Additionally, some benchmarks focus on real-world program-based tool use, such as DS-1000 (Lai et al., 2023), ODEX (Wang et al., 2023c), NumpyEval (Zan et al.), and TorchDataEval (Zan et al., 2022a). These benchmarks are designed to evaluate how well LLMs can handle specific libraries and programming scenarios, simulating more realistic and complex coding tasks. However, these benchmarks often focus on simple intents and use a limited number of specific function calls per programming task, making their evaluations less challenging and realistic. Meanwhile, there has been another line of work on multi-programming-language code generation. For example, HumanEval-X (Zheng et al., 2023), MultiPL-E (Cassano et al., 2023), and CodeScope (Yan et al., 2023) extend Python-only programming benchmarks via code translation, without considering programming-language-centric downstream scenarios. While there are some benchmarks addressing language-specific limitations like ClassEval (Du et al., 2023) and OOP (Wang et al., 2024b), their tasks are limited in terms of quantity, complexity, and diversity. Later, benchmarks like RepoBench (Liu et al.), CrossCodeEval (Ding et al., 2024), CoderEval (Yu et al., 2024), and SWE-bench (Yang et al.) are designed to evaluate the performance of a code agent framework, which includes iterated prompting, real-time environment interaction, and long-context exploration. Our benchmark focuses on evaluating the fundamental code generation capability of LLMs, which is also an essential path toward strong code agents. Additionally, SWE-bench is constructed from GitHub repositories with existing test cases, which limits the diversity of the tasks considered. In contrast, our collaborative LLM-human annotator procedure allows for generating tasks driven by real-world software engineering requirements, similar to the queries from StackOverflow, tackling a broader range of software tasks. Furthermore, our benchmark emphasizes some important aspects that have not been well discussed in the programming domain, like open-endedness (Hughes et al., 2024), multi-tool use (Qin et al., 2023), and instruction-following (Lou et al., 2023).

E BIGCODEBENCH-HARD

Running the full set of BigCodeBench will be burdensome for common users, especially when evaluating a large model on both BigCodeBench-Complete and BigCodeBench-Instruct. In order to save budgets, we release a minimal high-quality subset of BigCodeBench-Hard, serving as a proxy for the full set.

As illustrated in Figure 8, the workflow to construct BigCodeBench-Hard is mainly inspired by MixEval (Ni et al., 2024), which utilizes a small number of benchmark samples to align user-facing evaluation. While MixEval focuses on general-domain evaluation and considers only code generation tasks with minimal samples from MBPP and HumanEval, we extend the idea to make code generation evaluation more user-centric. Specifically, we follow these steps to create BigCodeBench-Hard:

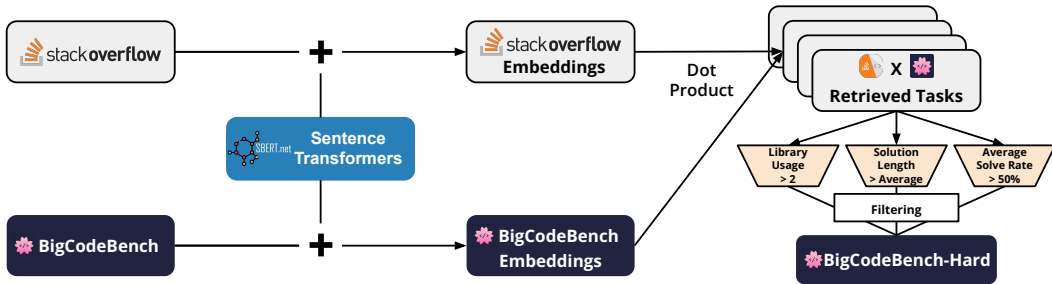


Figure 8: BigCodeBench-Hard construct workflow.

First, we choose an anonymized archive of Stack Overflow that has been preprocessed by the BigCode community. Details of the preprocessing can be found in the StarCoder2 (Lozhkov et al., 2024). The archive contains 10.4 million questions and answers, covering diverse programming languages and topics, making it a good source of user queries.

To bridge the query source and BigCodeBench, we leverage all-mpnet-base-v2, a pre-trained sentence embedding model recommended by the Sentence Transformers documentation (Reimers, 2019). This model, trained on a mixture of text and code data, is suitable for identifying similarities between programming queries and BigCodeBench tasks.

We use the model to retrieve the most similar tasks for each query in the Stack Overflow archive, ranking them by the dot product between normalized embeddings. Based on manual inspection of the retrieved tasks, we conclude that a similarity score above 0.7 is a good threshold for task selection. By applying this threshold, we obtain 6,895 queries and 626 BigCodeBench tasks after deduplication.

We illustrate the alignment between the Stack Overflow queries (Figure 9) and the BigCodeBench tasks (Figure 10). As shown in the figures, both the query and the task prompt revolve around web scraping to extract hyperlinks from web pages, using Python libraries to handle HTTP requests and parse HTML. Both involve interaction with CSV files to either read input URLs or write output data. While the specific implementation details differ, the core objective of extracting and handling hyperlink data from web pages is a shared aspect, aligning their overall scope closely.

However, the retrieved 626 tasks are still infeasible for evaluation. To improve evaluation efficiency, we further filter the tasks by difficulty. Unlike the construction of MixEval-Hard, we define the following more explainable criteria: (1) **Library Usage**: Each task in BigCodeBench emphasizes the compositional reasoning ability for coding and requires the use of at least two libraries. For BigCodeBench-Hard, we keep only the tasks that require more than two libraries, challenging the models to choose more diverse function calls as tools to solve the tasks; (2) **Solution Length**: We set the threshold at 426 tokens, which is the average solution length of the tasks in BigCodeBench. The ground-truth solution provides a reference for the task complexity, and tasks with longer solutions are more challenging to solve; and (3) **Solve Rate**: We compute the solve rate per task based on all the evaluated models on the leaderboard. The solve rate is defined as the number of models that can solve the task divided by the total number of models. Specifically, we deem tasks with a solve rate below 50% as hard tasks.

Through comparison, we notice that the model performance on BigCodeBench-Hard differs significantly from the one on the full set of BigCodeBench. We suggest that these differences arise from the imbalanced distribution of target domains and a large number of easy tasks in BigCodeBench, resulting in a slight misalignment between the evaluation and user-facing tasks. For example, GPT-4o-2024-05-13 and GPT-4o-0613 may be overfitting to the easy tasks in BigCodeBench, leading to low performance on BigCodeBench-Hard.

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```

I have a Python script that imports a list of url's from a CSV named list.csv, scrapes them and outputs
any anchor text and href links found on each url from the csv:

(For reference the list of urls in the csv are all in column A)

...
from requests_html import HTMLSession
from urllib.request import urlopen
from bs4 import BeautifulSoup
import requests
import pandas
import csv

contents = []
with open('list.csv','r') as csvf: # Open file in read mode
    urls = csv.reader(csvf)
    for url in urls:
        contents.append(url) # Add each url to list contents

for url in contents:
    page = urlopen(url[0]).read()
    soup = BeautifulSoup(page, "lxml")

    for link in soup.find_all('a'):
        if len(link.text)>0:
            print(url, link.text, '-', link.get('href'))

...

The output results look something like this where <https://www.example.com/csv-url-one/> and
<https://www.example.com/csv-url-two/> are the url's in column A in the csv:

...
[https://www.example.com/csv-url-one/] Creative - https://www.example.com/creative/
[https://www.example.com/csv-url-one/] Web Design - https://www.example.com/web-design/
[https://www.example.com/csv-url-two/] PPC - https://www.example.com/ppc/
[https://www.example.com/csv-url-two/] SEO - https://www.example.com/seo/

...

The issue is i want the output results to look more like this i.e not repeatedly print the url in the CSV
before each result AND have a break after each line from the CSV:

...
[https://www.example.com/csv-url-one/]
Creative - https://www.example.com/creative/
Web Design - https://www.example.com/web-design/

[https://www.example.com/csv-url-two/]
PPC - https://www.example.com/ppc/
SEO - https://www.example.com/seo/

...

Is this possible?

Thanks

```

Figure 9: StackOverflow user query.

```

import requests
from urllib.parse import urljoin
from bs4 import BeautifulSoup
import csv

def task_func(
    url: str,
    base_url: str = "https://www.example.com",
    csv_file: str = "scraped_data.csv",
) -> int:
    """
    This function scrapes a webpage for all hyperlinks and saves them as absolute URLs to a CSV file.

    Parameters:
    - url (str): The relative URL of the webpage to scrape.
    - base_url (str, optional): The base URL of the website to prepend to relative links. Defaults to
    'https://www.example.com'.
    - csv_file (str, optional): The filename for the CSV file where the links will be saved. Defaults to
    'scraped_data.csv'.

    Returns:
    - int: The number of unique absolute links scraped from the webpage.

    Requirements:
    - requests
    - urllib.parse.urljoin
    - bs4.BeautifulSoup
    - csv

    Examples:
    >>> task_func('/mywebpage')
    5
    >>> task_func('/anotherpage', base_url='https://www.different.com', csv_file='other_links.csv')
    8
    """

```

Figure 10: BigCodeBench task prompt.

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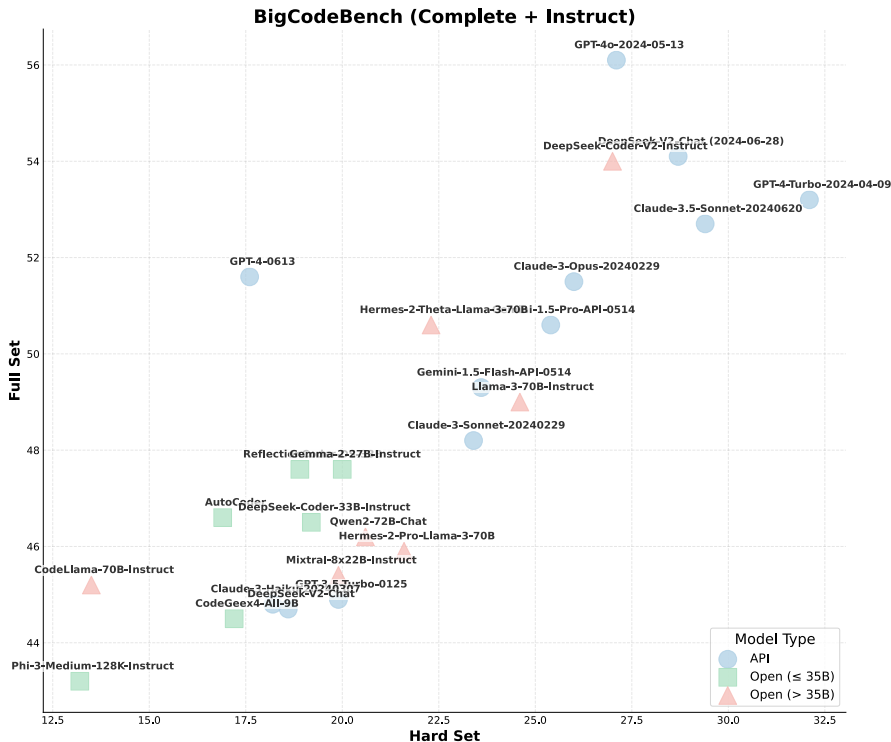


Figure 11: BigCodeBench rankings v.s. BigCodeBench-Hard rankings

To validate the effectiveness of BigCodeBench-Hard, we use a private leaderboard, [SEAL-Coding](#) curated by Scale AI, as a reference. The SEAL-Coding leaderboard is designed to evaluate models on a set of user-facing tasks across various application domains and programming languages. Specifically, SEAL-Coding compares **four of the best closed LLMs on Python**, with the following rankings: (1) **GPT-4-Turbo Preview**, (2) **Claude 3.5 Sonnet**, (3) **GPT-4o**, and (4) **Gemini 1.5 Pro (May 2024)**. These rankings align with our results based on the average score of the Complete and Instruct splits of BigCodeBench-Hard, indicating that BigCodeBench-Hard is more user-centric and challenging for model evaluation.

We encourage the community to use BigCodeBench-Hard when the budget is limited, and the evaluation needs to be more user-centric. Additionally, we note that BigCodeBench-Hard can be dynamic by design, depending on user queries and the evaluated models. We can periodically update BigCodeBench-Hard to keep the evaluation challenging and user-centric.

For dataset contributions and evaluation modifications, the most efficient way to reach us is via GitHub pull requests. For more questions, please contact **REDACTED** and **REDACTED** Project, who are responsible for maintenance.

F LONG-TERM ROADMAP AND CALL FOR CONTRIBUTIONS

In this section, we share a long-term roadmap to address the limitations of BigCodeBench, and sustainably build with the community. We believe that program-aided language models (Gao et al., 2023) for task completion and reasoning provide the possibility towards artificial general intelligence. Our goal is to provide the community with the most open, reliable, and scalable evaluations to truly understand the fundamental capabilities of LLMs for programming, pinpointing the ways to unleash their power.

F.1 LIMITATIONS

Given the limited time and budget we have to develop the initial benchmark, we have foreseen several limitations and aim to address them step-by-step.

Multilingualism One of the main limitations is that `BigCodeBench` is Python-only and cannot be easily extended to other programming languages. As the function calls are mostly language-specific, it is hard to find a package or library with exactly the same functionalities other than Python. However, given the fact that Python is the most flexible and popular programming language to automate various tasks, `BigCodeBench` may fulfill most of the community needs. In the meantime, we still seek efficient approaches to construct `BigCodeBench`-like programming tasks with tools in other languages, without much human effort.

Saturation Another potential criticism is that some LLMs can still perform reasonably well `BigCodeBench`, considering that the best models can only resolve no more than 30% of real-world GitHub issues on SWE-bench. One might indicate that our benchmark is not challenging enough. However, we note that the low performance on SWE-bench is likely due to the under-specified instructions and misaligned test cases⁵. Compared to SWE-bench, we tend to make the programming tasks much less ambiguous and ensure that the authors can pass their own solutions during annotation.

Reliability During the execution-based evaluation, we notice that some test cases are flaky (Luo et al., 2014), which results in uncertainty across multiple test runs without any code changes. We have progressively resolved some identified issues, such as missing setup of random states and improper removal of non-existent files. However, the remaining cases are trickier. For example, the socket query can be timed out or refused due to the unstable connection. With that being said, we try our best to make the uncontrollable changes of Pass@1 under 0.6%. We plan to continually enhance the reliability of all test cases, with the help of the community. To maintain the high reproducibility, we host a real-time code execution sandbox in the Hugging Face space.

Rigorousness While we achieve high test coverage for the ground-truth solutions in `BigCodeBench`, it does not guarantee that any code generated by LLMs will be correctly assessed against existing test cases. Previous works like EvalPlus (Liu et al., 2024) have attempted to extend the limited test cases by augmenting the input-output pairs via LLM- and mutation-based strategies. However, it is challenging to adapt EvalPlus to the test harness in `BigCodeBench`, as the harness only examines the expected program behaviors during the runtime (e.g., mocking tests). Furthermore, the function calls used to pass test cases by LLMs are more nondeterministic, making traditional test generation (Anand et al., 2013) methods cover all possible scenarios. Therefore, we still consider LLM-based test generation (Wang et al., 2024a) promising, but with proper designs. Specifically, a possible approach is to collect all the generated solutions that pass the current test cases and make a capable LLM (e.g., GPT-4o) harness with self-refinement in a sandbox environment.

Generalization One intuitive question is “How well do the models generalize to the unseen tools and tasks?” Current `BigCodeBench` only covers the common libraries and daily programming tasks. It will be more interesting to benchmark models on the programming tasks that use emerging libraries like `transformers` and `langchain`. Crafting new high-quality programming tasks requires huge effort, as demonstrated in this paper. There are two efficient approaches for building a programming benchmark for model generalization. First, we can instruction tune an LLM on `BigCodeBench` data with additional information of libraries and function calls. The trained model is expected to generate programming tasks with proper test cases based on the given library or function call details. However, the quality of such data synthesis is unknown, making the practicability questionable. Another way is to replace the function calls and libraries in `BigCodeBench` with the synthetic names, simulating the unseen ones. A similar approach (Zan et al., 2022b) has been used for code generation on unknown libraries. Although this method may lose the naturalness of software development, the construction process is more controllable and practical.

Evolution Naturally, the libraries can be obsolete or updated (Lamothe et al., 2021), which means that the source code data for model training will constantly evolve. Thus, the models may not

⁵<https://github.com/princeton-nlp/SWE-bench/issues/72>

1404 memorize function calls from a deprecated library version. This poses a challenge for any tool-
 1405 dependent programming benchmarks to correctly examine the model capability without periodic
 1406 updates. Another related concern is the test set contamination issue due to the evolving training data.
 1407 It is suggested to have both a public set and a private set for better evaluation in a recent blog⁶. For
 1408 future releases, we aim to perform the benchmark evolution both publicly and privately, and host the
 1409 private test set internally.

1410 **Interaction** Recent interests are around the concept of *LLMs as Agents* (Xi et al., 2023), which
 1411 is deemed as a way towards artificial general intelligence. Specifically, LLMs will be grounded
 1412 in a less constrained sandbox environment, where they can interact with any given applications,
 1413 such as the web browser and terminal. The environment can help unlock the capabilities like self-
 1414 debugging (Chen et al., 2023) and self-reflection (Shinn et al., 2024). We tend to work in this direction
 1415 and see how well *LLMs as Agents* can perform on BigCodeBench.

1416 **Diversity** There might be some concerns regarding the diversity of Python libraries covered by
 1417 BigCodeBench. While we agree that BigCodeBench can be extended with more domain-
 1418 specific libraries like the ones in SciCode (Tian et al., 2024), we believe that the usage of popular
 1419 libraries can be more aligned with real-world software development and maximally benefit the
 1420 community. In addition, due to the limited number of domain experts participating in our data
 1421 annotation, they may not have enough knowledge of the latest or domain-specific libraries. Annotating
 1422 the programming tasks involved with such libraries may result in errors and ambiguities. Furthermore,
 1423 the emerging libraries are immature and usually propose breaking changes, posing challenges to
 1424 constructing programming tasks with stable APIs.

1425 F.2 BIGCODEBENCH-OOD

1426 We will construct BigCodeBench-OOD, a variant of BigCodeBench that assesses the general-
 1427 ization ability on out-of-distribution (OOD) libraries and programming tasks (Zhou et al., 2023).
 1428 We note that any features that do not frequently appear can be considered OOD. We tend to build
 1429 BigCodeBench-OOD with two different types of OOD: (1) Completely synthetic features; and (2)
 1430 Real but long-tail features. The first type can represent the private libraries that are unknown to the
 1431 models, and the latter one may represent the ones trending in the recent programming practice but
 1432 have not yet played major roles in the training data.

1433 F.3 BIGCODEBENCH-INTERACT

1434 To examine the agent-centric programming ability, we will adapt BigCodeBench to an interactive
 1435 sandbox environment, with a list of applications that can help models program and repair iteratively as
 1436 humans. Unlike existing programming benchmarks such as HumanEval and MBPP, BigCodeBench
 1437 covers a wide range of tasks that require profound programming knowledge. Without the proper
 1438 understanding, models are likely to fail in debugging and repair. There are potentially two options
 1439 for the evaluation. One naive option is to allow models to see the backtrace of how they fail in the
 1440 test cases, which can guide them to repair the bugs with a clear goal. A more challenging setup is to
 1441 make models fix bugs independently without seeing any backtrace. Capable models are expected to
 1442 resolve issues by generating their own test cases and inspecting the execution outcomes.

1443 F.4 BIGCODEBENCH-EVOLVED

1444 To mitigate the effects of API evolution, we consider LLM-based API updates as a promising
 1445 approach to explore. However, several challenges need to be addressed from the software engineering
 1446 aspect. First, there are many types of API evolution in Python. According to the study on 288 releases
 1447 of six popular Python libraries (Zhang et al., 2020), there are 14 different types of API evolution (e.g.,
 1448 class removal, method removal, parameter reordering, and field addition). Among them, 11 types
 1449 are breaking changes, meaning they will directly affect the program’s behavior. Resolving the API
 1450 removal requires non-trivial effort, as the evolved APIs may not have any replacement in the future
 1451 library version. Second, Wang et al. (2020) mention that a significant number of deprecated APIs
 1452

1453 ⁶<https://www.jasonwei.net/blog/evals>

1458 are not documented properly, making it hard for library users to mitigate the usage of deprecated
1459 APIs. To potentially mitigate all these issues, we suggest combining static program analysis for
1460 library versions and multi-turn LLM interaction. Specifically, we can utilize static program analysis
1461 to compare APIs across versions and make LLMs to identify the potential changes, even if they are
1462 not officially documented. Then, we will apply rule-based methods to analyze whether the target
1463 programming tasks inside BigCodeBench have deprecated APIs. For the ones to be updated, we
1464 will further provide LLMs with the new library documentation and identified API changes, let them
1465 propose new implementations for the ground-truth solutions, and revise the deprecated APIs inside
1466 test cases. Regarding the cases of API removal, LLMs may need more turns to generate the valid
1467 implementation, as there is no reference for the replacement. The revision To automatically validate
1468 the updated solutions and test cases, we will ground LLMs inside the code sandbox for multi-turn
1469 execution.

1470 G ARTIFACTS

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Table 5: Artifacts for reproducibility.

Name	Public Link or Endpoint
<i>BigCodeBench (v0.2.0)</i>	
GitHub Hugging Face Croissant	REDACTED REDACTED REDACTED
<i>Annotation Framework</i>	
GitHub	REDACTED
<i>Evaluation Framework</i>	
GitHub PyPI	REDACTED REDACTED
<i>Datasets for Comparisons</i>	
HumanEval	https://github.com/openai/human-eval/blob/master/data/HumanEval.jsonl.gz
ODEX	https://github.com/zorazrw/odex/tree/master/data
DS-1000	https://github.com/xlang-ai/DS-1000/blob/main/data/ds1000.jsonl.gz
APPS	https://github.com/hendrycks/apps
APIBench	https://github.com/ShishirPatil/gorilla/tree/main/data/apibench
MBPP	https://github.com/google-research/google-research/tree/master/mbpp
NumpyEval	https://github.com/microsoft/PyCodeGPT/tree/main/cert/pandas-numpy-eval
PandasEval	https://github.com/microsoft/PyCodeGPT/tree/main/cert/pandas-numpy-eval
TorchDataEval	https://github.com/microsoft/PyCodeGPT/blob/main/apicoder/private-eval/data/real_torchdata_eval_v3.jsonl.gz
<i>Models for Evaluations</i>	
GPT-4o	gpt-4o
GPT-4-Turbo	gpt-4-turbo
GPT-4	gpt-4
GPT-3.5-Turbo	gpt-3.5-turbo
Claude-3-Opus	claude-3-opus
Claude-3-Sonnet	claude-3-sonnet
Claude-3-Haiku	claude-3-haiku
DeepSeek-V2-Chat	deepseek-chat (API, 32K)
Mistral-Large	mistral-large-2402
Mistral-Small	mistral-small-2402
DeepSeek-Coder-33b-Instruct	https://huggingface.co/deepseek-ai/deepseek-coder-33b-instruct
DeepSeek-Coder-6.7b-Instruct	https://huggingface.co/deepseek-ai/deepseek-coder-6.7b-instruct
DeepSeek-Coder-1.3b-Instruct	https://huggingface.co/deepseek-ai/deepseek-coder-1.3b-instruct
CodeLlama-70B-Instruct	https://huggingface.co/codellama/CodeLlama-70b-instruct-hf
CodeLlama-34B-Instruct	https://huggingface.co/codellama/CodeLlama-34b-instruct-hf
CodeLlama-13B-Instruct	https://huggingface.co/codellama/CodeLlama-13b-instruct-hf
CodeLlama-7B-Instruct	https://huggingface.co/codellama/CodeLlama-7b-instruct-hf
Llama-3-70B-Instruct	https://huggingface.co/meta-llama/Meta-Llama-3-70B-Instruct
Llama-3-8B-Instruct	https://huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct
Qwen2-72B-Instruct	https://huggingface.co/Qwen/Qwen2-72B-Instruct
Qwen2-7B-Instruct	https://huggingface.co/Qwen/Qwen2-7B-Instruct
Qwen2-57B-A14B	https://huggingface.co/Qwen/Qwen2-57B-A14B
CodeQwen1.5-7B-Chat	https://huggingface.co/Qwen/CodeQwen1.5-7B-Chat
Qwen1.5-110B-Chat	https://huggingface.co/Qwen/Qwen1.5-110B-Chat
Qwen1.5-72B-Chat	https://huggingface.co/Qwen/Qwen1.5-72B-Chat
Qwen1.5-32B-Chat	https://huggingface.co/Qwen/Qwen1.5-32B-Chat
Yi-1.5-34B-Chat	https://huggingface.co/01-ai/Yi-1.5-34B-Chat
Yi-1.5-9B-Chat	https://huggingface.co/01-ai/Yi-1.5-9B-Chat
Yi-1.5-6B-Chat	https://huggingface.co/01-ai/Yi-1.5-6B-Chat
Mixtral-8x22B-Instruct	https://huggingface.co/mistralai/Mixtral-8x22B-Instruct-v0.1
Magicalor-S-DS	https://huggingface.co/ise-uiuc/Magicalor-S-DS-6.7B
CodeGemma-7B-Instruct	https://huggingface.co/google/codegemma-7b-it
StarCoder2-Instruct	https://huggingface.co/bigcode/starcoder2-15b-instruct-v0.1
Granite-34B-Code-Instruct	https://huggingface.co/ibm-granite/granite-34b-code-instruct
Granite-20B-Code-Instruct	https://huggingface.co/ibm-granite/granite-20b-code-instruct
Granite-8B-Code-Instruct	https://huggingface.co/ibm-granite/granite-8b-code-instruct
Granite-3B-Code-Instruct	https://huggingface.co/ibm-granite/granite-3b-code-instruct
CodeLlama-70B-Base	https://huggingface.co/codellama/CodeLlama-70b-hf
CodeLlama-34B-Base	https://huggingface.co/codellama/CodeLlama-34b-hf
CodeLlama-13B-Base	https://huggingface.co/codellama/CodeLlama-13b-hf
CodeLlama-7B-Base	https://huggingface.co/codellama/CodeLlama-7b-hf
Llama-3-70B-Base	https://huggingface.co/meta-llama/Meta-Llama-3-70B
Llama-3-8B-Base	https://huggingface.co/meta-llama/Meta-Llama-3-8B
DeepSeek-Coder-base-33B	https://huggingface.co/deepseek-ai/deepseek-coder-33b-base
DeepSeek-Coder-base-6.7B	https://huggingface.co/deepseek-ai/deepseek-coder-6.7b-base
DeepSeek-Coder-base-1.3B	https://huggingface.co/deepseek-ai/deepseek-coder-1.3b-base
CodeQwen1.5-7b	https://huggingface.co/Qwen/CodeQwen1.5-7B
Yi-1.5-34B	https://huggingface.co/01-ai/Yi-1.5-34B
Yi-1.5-9B	https://huggingface.co/01-ai/Yi-1.5-9B
Yi-1.5-6B	https://huggingface.co/01-ai/Yi-1.5-6B
Mixtral-8x22B-Base	https://huggingface.co/mistralai/Mixtral-8x22B-v0.1
CodeGemma-7B	https://huggingface.co/google/codegemma-7b
CodeGemma-2B	https://huggingface.co/google/codegemma-2b
StarCoder2-15B	https://huggingface.co/bigcode/starcoder2-15b
StarCoder2-7B	https://huggingface.co/bigcode/starcoder2-7b
StarCoder2-3B	https://huggingface.co/bigcode/starcoder2-3b
Granite-34B-Code-Base	https://huggingface.co/ibm-granite/granite-34b-code-base
Granite-20B-Code-Base	https://huggingface.co/ibm-granite/granite-20b-code-base
Granite-8B-Code-Base	https://huggingface.co/ibm-granite/granite-8b-code-base
Granite-3B-Code-Base	https://huggingface.co/ibm-granite/granite-3b-code-base

H TOOL STATISTICS

H.1 ANALYSIS

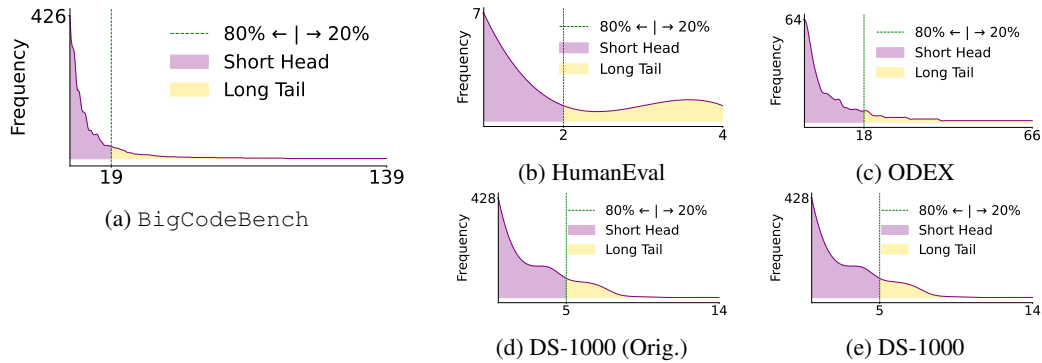


Figure 12: Library density comparisons. We sort the libraries by frequency count, showcasing the long-tail distribution to highlight the broad diversity within BigCodeBench.

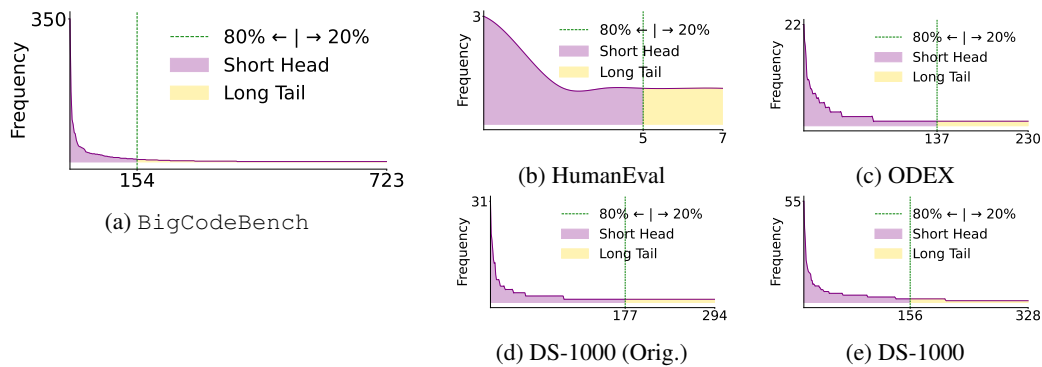


Figure 13: Function call density comparisons. We sort function calls by frequency count, showcasing the long-tail distribution to highlight the broad diversity within BigCodeBench.

H.2 COMPARISON TO EXISTING PROGRAMMING BENCHMARKS

Table 6: Depth (Complexity — Solution Characters) and breadth (Diversity – Function Calls) comparisons to existing programming benchmarks in Python.

Benchmark	Complexity	Diversity
APPS (Hendrycks et al., 2021)	352.9	137
DS-1000 (Lai et al., 2023)	138.1	328
ODEX (Wang et al., 2023c)	50.4	230
APIBench (Patil et al., 2023)	77.5	171
MBPP (Austin et al., 2021)	181.1	51
NumpyEval (Zan et al., 2022b)	30.1	52
PandasEval (Zan et al., 2022b)	45.8	12
HumanEval (Chen et al., 2021)	180.9	7
TorchDataEval (Zan et al., 2022a)	52.8	6
BigCodeBench	426.0	723

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H.3 VERSION CONTROL

```
pandas==2.0.3
scikit-learn==1.3.1
requests==2.31.0
matplotlib==3.7.0
seaborn==0.13.2
numpy==1.21.2
numba==0.55.0
cryptography==38.0.0
scipy==1.7.2
nltk==3.8
pytz==2023.3.post1
networkx==2.6.3
statsmodels==0.14.0
lxml==4.9.3
psutil==5.9.5
Django==4.2.7
selenium==4.15.
Pillow==10.3.0
beautifulsoup4==4.8.2
datetime==5.5
python-docx==1.1.0
openpyxl==3.1.2
Levenshtein==0.25.0
PyYAML==6.0.1
wordninja==2.0.0
Faker==20.1.0
tensorflow==2.11.1
wordcloud==1.9.3
pytesseract==0.3.10
chardet==5.2.0
python-dateutil==2.9.0
blake3==0.4.1
dnspython==2.6.1
flask==3.0.3
Flask-Mail==0.9.1
flask_login==0.6.3
flask_restful==0.3.10
flask_wtf==1.2.1
folium==0.16.0
geopy==2.4.1
keras==2.11.0
librosa==0.10.1
mechanize==0.4.9
prettytable==3.10.0
pycryptodome==3.14.1
python_http_client==3.3.7
Requests==2.31.0
requests_mock==1.11.0
rsa==4.9
sendgrid==6.11.0
soundfile==0.12.1
texttable==1.7.0
Werkzeug==3.0.1
WTForms==3.1.2
xlrd==2.0.1
xlwt==1.3.0
xmldict==0.13.0
python-Levenshtein-wheels
gensim==4.3.2
sympy==1.12
pyfakefs==5.4.1
textblob==0.18.0
docxtempl==0.11.5
statsmodels==0.14.0
pyquery==1.4.3
holidays==0.29
scikit-image==0.18.0
natsort==7.1.1
shapely==2.0.4
geopandas==0.13.2
opencv-python-headless==4.9.0.80
xlrd==2.0.1
pytest==8.2.0
wikipedia==1.4.0
```

H.4 DOMAIN CLASSIFICATION

```
{
  "Crypto": "Cryptography",
  "PIL": "Visualization",
  "array": "General",
  "base64": "Cryptography",
  "binascii": "Cryptography",
  "bisect": "General",
  "blake3": "Cryptography",
  "bs4": "Network",
```

```

1674     "calendar": "Time",
1675     "cgi": "Network",
1676     "chardet": "Network",
1677     "cmath": "Computation",
1678     "codecs": "Cryptography",
1679     "collections": "General",
1680     "cryptography": "Cryptography",
1681     "csv": "System",
1682     "ctypes": "System",
1683     "datetime": "Time",
1684     "dateutil": "Time",
1685     "difflib": "General",
1686     "django": "Network",
1687     "docx": "System",
1688     "email": "Network",
1689     "faker": "General",
1690     "flask": "Network",
1691     "flask_login": "Network",
1692     "flask_mail": "Network",
1693     "flask_restful": "Network",
1694     "fnmatch": "General",
1695     "folium": "Visualization",
1696     "func tools": "General",
1697     "geopy": "Network",
1698     "getpass": "System",
1699     "glob": "System",
1700     "gzip": "System",
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1702     "heapq": "General",
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1706     "importlib": "General",
1707     "inspect": "General",
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1709     "ipaddress": "Network",
1710     "itertools": "General",
1711     "json": "System",
1712     "keras": "Computation",
1713     "librosa": "Computation",
1714     "logging": "System",
1715     "lxml": "Network",
1716     "math": "Computation",
1717     "matplotlib": "Visualization",
1718     "mechanize": "Network",
1719     "mimetypes": "Network",
1720     "multiprocessing": "System",
1721     "nltk": "Computation",
1722     "numpy": "Computation",
1723     "openpyxl": "System",
1724     "operator": "General",
1725     "os": "System",
1726     "pandas": "Computation",
1727     "pathlib": "System",
1728     "pickle": "System",
1729     "pkgutil": "General",
1730     "platform": "System",
1731     "prettytable": "General",
1732     "psutil": "System",
1733     "pytesseract": "Computation",
1734     "pytz": "Time",
1735     "queue": "General",
1736     "random": "General",
1737     "re": "General",
1738     "requests": "Network",
1739     "rsa": "Cryptography",
1740     "scipy": "Computation",
1741     "seaborn": "Visualization",
1742     "secrets": "Cryptography",
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1745     "shutil": "System",
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1764     "turtle": "Visualization",
1765     "types": "General",

```



```

1728
1729 "unicodedata": "General",
1730 "urllib": "Network",
1731 "uuid": "General",
1732 "warnings": "General",
1733 "werkzeug": "Network",
1734 "wordninja": "Computation",
1735 "wtforms": "Network",
1736 "xlwt": "System",
1737 "xml": "Network",
1738 "xmldict": "Network",
1739 "yaml": "System",
1740 "zipfile": "System",
1741 "Levenshtein": "Computation",
1742 "ast": "General",
1743 "configparser": "System",
1744 "cv2": "Computation",
1745 "decimal": "General",
1746 "enum": "General",
1747 "errno": "System",
1748 "flask_wtf": "Network",
1749 "ftplib": "Network",
1750 "gensim": "Computation",
1751 "geopandas": "Computation",
1752 "holidays": "Time",
1753 "mpl_toolkits": "Visualization",
1754 "natsort": "General",
1755 "pyquery": "Network",
1756 "python_http_client": "Network",
1757 "regex": "General",
1758 "shapely": "Computation",
1759 "shlex": "System",
1760 "signal": "System",
1761 "skimage": "Computation",
1762 "sympy": "Computation",
1763 "textblob": "Computation",
1764 "typing": "General",
1765 "wikipedia": "Network",
1766 "wordcloud": "Visualization",
1767 "zlib": "System",
1768 "aspose": "System",
1769 "builtins": "General",
1770 "locale": "System",
1771 "imp": "System",
1772 "docxtpl": "System",
1773 "selenium": "Network",
1774 "IPython": "Computation",
1775 "filecmp": "System",
1776 "multidict": "General",
1777 "sqlalchemy": "System",
1778 "obspy": "Computation",
1779 "pprint": "General",
1780 "xlrd": "System",
1781 "argparse": "General",
1782 "torch": "Computation",
1783 "copy": "General"
1784 }

```

I DETAILED BENCHMARK CONSTRUCTION

I.1 DATA SYNTHESIS PROMPT

```

1767 Based on the following simple example, write more complex scenarios and invoke multiple Python libraries ←
1768 to solve each problem.
1769 The written intent should align with a more specific and practical scenario, but should still be easy to ←
1770 do functional correctness assertion.
1771 For each scenario, write a single Python function with the rewritten intent.
1772 Please include requirements and terminal-based input-output examples in the function docstring.
1773 The function should contain complex logic like if-else statements and loops.
1774 You have to use more than three Python libraries for a scenario. Write imports and variable definitions ←
1775 outside the function.
1776 Try to avoid using web APIs if possible.
1777 If there are any constants (e.g. strings and numeric values) used in the functions, you need to declare ←
1778 them before the function.
1779 If data is used, you need to provide sample data in the comment.
1780 Try to return values for correctness assertion.
1781 Each programming scenario and intent should be separated by the special token `GPT_ODEX_BREAK`.
1782
1783 Generate two examples with two scenarios:
1784 {"task_id": 4530069, "prompt": "def f_4530069():\n\treturn ", "suffix": "", "canonical_solution": "←
1785     datetime.now(pytz.utc)", "test_start": "\nimport pytz\nimport time\nfrom datetime import datetime, ←
1786     timezone\n\ndef check(candidate):", "test": ["\n    assert (candidate() - datetime(1970, 1, 1).←
1787     replace(tzinfo=timezone.utc)).total_seconds() - time.time() <= 1\n"], "entry_point": "f_4530069", "←
1788     intent": "get a value of datetime.today() in the UTC time zone", "library": ["datetime", "pytz", "←
1789     time"]}
1790
1791 Scenario 1:
1792 pandas, pytz, datetime, random, matplotlib

```

```

1782
1783 ```python
1784 import pandas as pd
1785 import pytz
1786 from datetime import datetime
1787 from random import randint
1788 import matplotlib.pyplot as plt
1789
1790 # Constants
1791 CITIES = ['New York', 'London', 'Beijing', 'Tokyo', 'Sydney']
1792 WEATHER_CONDITIONS = ['Sunny', 'Cloudy', 'Rainy', 'Snowy', 'Stormy']
1793
1794 # Time zones for the cities
1795 TIMEZONES = {
1796     'New York': 'America/New_York',
1797     'London': 'Europe/London',
1798     'Beijing': 'Asia/Shanghai',
1799     'Tokyo': 'Asia/Tokyo',
1800     'Sydney': 'Australia/Sydney'
1801 }
1802
1803 def generate_weather_report(utc_datetime):
1804     """
1805     Generate a report of weather conditions for a list of cities across various
1806     time zones at a given time (UTC).
1807
1808     Parameters:
1809     utc_datetime (datetime): The datetime in UTC.
1810
1811     Returns:
1812     DataFrame: A pandas DataFrame with weather conditions for the cities.
1813
1814     Requirements:
1815     - pandas
1816     - pytz
1817     - datetime
1818     - random
1819     - matplotlib.pyplot
1820
1821     Example:
1822     >>> utc_time = datetime(2023, 6, 15, 12, 0, 0, tzinfo=pytz.UTC)
1823     >>> report = generate_weather_report(utc_time)
1824     >>> print(report)
1825     >>> report['Weather Condition'].value_counts().plot(kind='bar')
1826     """
1827     report_data = []
1828
1829     for city in CITIES:
1830         city_tz = pytz.timezone(TIMEZONES[city])
1831         city_time = utc_datetime.astimezone(city_tz)
1832         weather = WEATHER_CONDITIONS[randint(0, len(WEATHER_CONDITIONS)-1)]
1833         report_data.append([city, city_time, weather])
1834
1835     report_df = pd.DataFrame(report_data, columns=['City', 'Local Time', 'Weather Condition'])
1836
1837     return report_df
1838
1839 ```
1840
1841 `GPT_ODEX_BREAK`
1842
1843 Scenario 2:
1844 pytz, datetime, numpy, dateutil
1845 ```python
1846 import pytz
1847 from datetime import datetime
1848 import numpy as np
1849 from dateutil.parser import parse
1850
1851 # Constants
1852 LEAP_SECONDS = np.array([1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980,
1853     1981, 1982, 1983, 1985, 1988, 1990, 1993, 1994, 1997,
1854     1999, 2006, 2009, 2012, 2015, 2016, 2020])
1855
1856 def total_seconds_since_date(date_str, from_tz, to_tz):
1857     """
1858     Calculate the total seconds that have passed since a given datetime from the current time
1859     in different timezones considering the leap seconds.
1860
1861     Parameters:
1862     date_str (str): The date string in "yyyy-mm-dd hh:mm:ss" format.
1863     from_tz (str): The timezone of the given date string.
1864     to_tz (str): The timezone to which the current time should be converted.
1865
1866     Returns:
1867     int: The total seconds.
1868
1869     Requirements:
1870     - datetime
1871     - pytz
1872     - numpy
1873     - dateutil.parser
1874
1875     Example:
1876     >>> total_seconds_since_date('1970-01-01 00:00:00', 'UTC', 'America/New_York')

```

```

1836
1837 """
1838 from_tz = pytz.timezone(from_tz)
1839 to_tz = pytz.timezone(to_tz)
1840 given_date = parse(date_str).replace(tzinfo=from_tz)
1841 current_date = datetime.now().astimezone(to_tz)
1842
1843 total_seconds = (current_date - given_date).total_seconds()
1844
1845 leap_years = LEAP_SECONDS[np.logical_and(LEAP_SECONDS >= given_date.year, LEAP_SECONDS <= current_date
1846 .year)]
1847 leap_seconds = len(leap_years)
1848
1849 total_seconds += leap_seconds
1850
1851 return int(total_seconds)
1852 """
1853
1854 Above is the illustration.
1855
1856 Generate five complex scenarios based on the following simple example:

```

1850 I.2 SEMI-AUTOMATIC PROGRAM REFACTORING AND TESTING CASE GENERATION

1852 I.2.1 PROGRAMMING TASK CLASSIFICATION PROMPT

```

1853 # Choose the most suitable labels for the given program:
1854 SQL
1855 CSV
1856 DataFrames
1857 Time
1858 JSON
1859 XML
1860 HTML
1861 Image
1862 Text
1863 Built-in Data Structure
1864 Analysis
1865 Networking
1866 Processing
1867 Visualization
1868 File Storage
1869 Encryption
1870
1871 # You should output the suitable labels in a list format, such as ["CSV", "DataFrames"].

```

1866 I.2.2 GUIDELINES

```

1868 ## Annotation Guideline:
1869
1870 You are given a function inside "function.py". The goal is to:
1871 1) refine the function including its docstrings in order to make the function more realistic and less
1872    ambiguous. This means when you see the function stub and docstring, you should be able to implement
1873    with exactly the same functionality with the given function body;
1874 2) write blackbox unit tests to ensure the functional correctness of the given function. You should also
1875    make the function easy to test.
1876
1877 ### Step1: Check Library Imports
1878
1879 #### Import Statement
1880
1881 - Remove the library imports that are not used in the code.
1882 - Import libraries before the function declaration.
1883
1884 #### Library Usage
1885
1886 - Check if the usage of these libraries is reasonable. For example, if the description asks to complete a
1887    functionality that can be implemented without any of these libraries, then the usage of these
1888    libraries APIs is not reasonable. You need to check Step 2 for more details to modify the description
1889    so that it can make use of the imported libraries.
1890
1891 ### Step2: Check Docstring
1892
1893 #### Description
1894
1895 - Check if the expression of the description is clear and concise. If not, you need to modify the
1896    description to make it clear and concise.
1897 - The description must mention the following five things:
1898   - Functionality
1899   - Input
1900   - Output to be returned
1901   - Requirements of the imported libraries/modules to be used
1902   - 1 or 2 examples of the input and output of the function
1903 - Mention the necessary data structure if the function requires data manipulation.
1904 - You must not change the overall functionality of the function, and remove any libraries/modules that are
1905    imported in the function to accommodate the blackbox testing.

```

```

1890
1891 ##### Input Parameters
1892 - Check if the function takes input parameters. If not, you need to modify the description and the
1893     function to make it take input parameters.
1894 ##### Example
1895 - Provide 1 or 2 examples of the input and output of the function.
1896 - ```bash
1897   >>> f_0("hello")
1898     "hello world"
1899   >>> f_0("I")
1900     "love you"
1901   ```
1902 - ```bash
1903   >>> f_0("image_1.jpg")
1904   <module 'matplotlib.pyplot'>
1905   >>> f_0("image_2.jpg")
1906   <module 'matplotlib.pyplot'>
1907   ```
1908 ##### Step 3: Check Function Implementation
1909 - Check if the function implementation is correct. If not, you need to repair the function implementation
1910     to make it correct.
1911 - Check if the function uses any constants.
1912   - If yes and the description has not mentioned any of them, you need to either leave off the argument so
1913     it takes the default value, or modify the description to mention them.
1914   - For example, for the 'plt.hist(counts, bins=np.arange(len(counts)+1)-0.5, rwidth=0.8)' in 'f_0', the
1915     description should mention the specific way to compute with 'len(counts)+1)-0.5' and use 'rwidth
1916     =0.8'.
1917 - Check if the function has the return values. If not, you need to modify the function to make it return
1918     the values for the test cases to check.
1919 - If the function requires to write or show some data, you shall either return the data or make the
1920     function take a path for file storage or a variable for data visualization. For example, if the
1921     function requires to show a plot, you must return the plot (via Axes).
1922 - If the function requires checking some properties and uses 'print()' to show the results, you need to
1923     modify this function to return these results. The revised function should amalgamate these properties
1924     with the preexisting return values, thereby facilitating more versatile utilization of the outputs
1925     in the rest of your code.
1926   - Consider this original function:
1927
1928 def check_properties(original_list):
1929     is_empty = not bool(original_list)
1930     print(f"Is the list empty? {is_empty}")
1931
1932     length = len(original_list)
1933     print(f"Length of the list is {length}")
1934
1935 check_properties([1, 2, 3, 4])
1936
1937 This function checks two properties of a list: whether it's empty and its length. It then prints these
1938     results. However, these results can't be used elsewhere in your program.
1939
1940 Now, let's modify the function to return these results:
1941
1942 def check_properties(original_list):
1943     is_empty = not bool(original_list)
1944     length = len(original_list)
1945
1946     return is_empty, length
1947
1948 list_empty, list_length = check_properties([1, 2, 3, 4])
1949
1950 print(f"Is the list empty? {list_empty}")
1951 print(f"Length of the list is {list_length}")
1952
1953 In this modified version, the function returns the two properties instead of printing them. This allows
1954     you to capture the returned values in list_empty and list_length variables and use them elsewhere in
1955     your program.
1956
1957 - If you return any formats of values (e.g. 'string'), make sure that you mention the format in the
1958     description. It is better for assessing the correctness of the function implementation.
1959 ##### Step4: Run The Function and Write Blackbox Test Cases
1960
1961 - The function is contained in a file named 'function.py', and you are required to write a blackbox
1962     testing function named 'run_tests()' that contains assertion-based blackbox test cases in 'test.py'.
1963 - If any of the following data types are used for manipulation, you need to manually design the data or
1964     utilize 3rd party libraries and websites (e.g. 'Faker' and 'unittest.mock') to generate or mock the
1965     test data. You can use the "file://" protocol to access the local HTML files, and any url request
1966     APIs should work correctly with this protocol. (See https://chat.openai.com/share/84ba0dc9-067d-4eb0-a4d4-d8f4a77ffa15)
1967
1968 - html (webpage, page link)
1969 - csv
1970 - json
1971 - xml
1972 - sql
1973 - image

```

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1997

```

- You should test the possible attributes of that written data. For example, if you return a plot, you
  need to test if the plot contains the correct title, x-axis, y-axis and data points.

- To formalize the test case writing, you need to write with the following function:

```python
def run_tests():
 suite = unittest.TestSuite()
 suite.addTest(unittest.makeSuite(TestCases))
 runner = unittest.TextTestRunner()
 runner.run(suite)

class TestCases(unittest.TestCase):
 def test_case_1(self):
 # Input 1: write your test case here.
 # provide a series of unit tests to test all attributes of the returned values
 pass

 def test_case_2(self):
 # Input 2: write your test case here.
 # Provide a series of unit tests to test all attributes of the returned values
 pass

 def test_case_3(self):
 # Input 3: write your test case here.
 # Provide a series of unit tests to test all attributes of the returned values
 pass

 # write more tests here
...
- Each blackbox test method should be tested with a unique input value and asserted for the return values.

Working

After reading the guideline, refine 'function.py' and write a single test program named 'run_tests()' in '
test.py', which should contain at least *five* different input cases.

When testing with data, you need to generate the data by yourself or use 3rd party libraries and websites
(e.g. 'Faker' and 'unittest.mock') to generate or mock the test data. For example, you should design
the html webpage to meet the functionality and test scenarios. For any numeric values, you need to
represent them in the data.

Make the test data as complex as possible to mimic the real-world data. For example, if the function
requires reading a csv file, you need to design the csv file to meet the functionality and test
scenarios.

You can not remove any libraries or modules used in the original function. However, you can add new
libraries or modules to the function.

Make sure you have tested all return values and the possible attributes of the written data.

Keep testing the function until you are satisfied with the function implementation and the test cases.

If any tested properties are not mentioned in the description, you need to modify the description to
mention them.

As we will provide the function stub for programmers to implement by their own, please make sure there is
no ambiguity in the description and the function implementation. If there is any ambiguity, you need
to modify the description and the function implementation to make it clear and concise. Think about
the possible questions that programmers may ask and try to answer them in the description.

Execute to make sure 'function.py' will pass all blackbox test cases. Otherwise, you need to modify the
function implementation to make it pass all blackbox test cases.

Refine 'function.py' and write blackbox tests in 'test.py'

Note that 'Faker' library has already been installed in the environment and you can use it freely.

Download refined 'function.py', written 'test.py' and created 'test_data.zip' if there exists.

```

### 1.3 HUMAN CURATION GUIDELINES

```

Annotation Guidelines

Environment Setup

You are given a file named 'requirements.txt', please set up a Python environment with version 3.8.10. You
can use Anaconda or Python Virtual Environment for this purpose.

Use the following command to install all required libraries:
```sh
pip install -U -r requirements.txt
```

Please note that this environment will be the same as the one used by OpenAI GPT-4 Advanced Data Analysis
(or Code Interpreter). Although it is expected that most APIs are stable, it is safer to use

```

1998 consistent library versions. You are encouraged to use more libraries covered in the requirements.txt ↩

1999 to enrich each sample.

2000

2001 ## Annotation Goal

2002 The goal is to:

2003 Refine the function, including its docstrings in order to make the function more realistic and less ↩

2004 ambiguous. This means when you see the function stub and docstring, you should be able to implement ↩

2005 exactly the same functionality with the given function body. Add more library APIs if necessary;

2006 Write additional black box unit tests to ensure the functional correctness of the given function. You ↩

2007 should consider as many corner cases as possible.

2008 ## Expected Annotation

2009 You are given a Python script to execute and annotate.

2010 We define the following terms:

2011 'Programming Problem' contains three parts:

2012 [Standalone] 'Import Statement'

2013 The imported libraries, submodules or functions should be used in the following function implementation.

2014 add missing libraries, submodules or functions if one is used but not imported.

2015 'Problem Function'

2016 'Function Signature' and its corresponding 'Docstring'

2017 The 'Function Name' should be obfuscated in the format of 'f\_[NUMBER]' to ensure anonymity. [NUMBER] ↩

2018 should be the one inside the file name.

2019 The docstrings (example can be found at Google Python Style Guide) should contain:

2020 A 'Functionality Description'.

2021 'Function Parameters' and their 'Function Parameters Descriptions'.

2022 2-3 'Running Examples' in Python Interpreter and their expected outputs.

2023 'Solution'

2024 The function implementation to fulfil the functionality described in the 'Docstring'.

2025 'Test Suite' contains three parts:

2026 [Standalone] 'Import Statement'

2027 The imported libraries, submodules or functions should be used in the following tests.

2028 [Standalone] 'TestCases' class

2029 The class should contain at least five distinct test cases.

2030 The test cases should be aligned with the docstring description. Test cases should not assert any ↩

2031 attributes which are not specifically mentioned.

2032 The test cases should cover as many branches in the 'Problem Function' as possible. In order to get the ↩

2033 complete coverage, you should use the command 'coverage run -m unittest f\_[NUMBER]\_[NAME].py && ↩

2034 coverage report -m'. Replace the 'f\_[NUMBER]\_[NAME].py' with the file name you are testing with. ↩

2035 Ignore the missing lines in the 'Test Suite'.

2036 'Programming Problem' should be able to pass all these test cases. This means the scripts should run ↩

2037 successfully without any failed test cases when you run 'python XXX.py' in the terminal.

2038 [Standalone] 'run\_tests' function

2039 The function should only contain the code helping to execute the test cases.

2040 ## Issues To Be Addressed

2041 You may notice the existence of the following issues in the given Python script:

2042 'Function Name' has not been obfuscated.

2043 Replace the name with 'f'.

2044 'Docstring' is unclear, ambiguous, impractical or not well aligned with 'Solution'.

2045 'Function Description' should describe a practical functionality.

2046 You should either refine the 'Function Description' or 'Solution'. Choose the one more feasible to be ↩

2047 done.

2048 Make sure at least 2 correct 'Running Examples' are included.

2049 'Solution' does not use all imported libraries or APIs.

2050 Try to refine the 'Programming Problem' so that the 'Function Description' implies the corresponding API ↩

2051 usage and such APIs are correctly invoked in 'Solution'.

2052 If (a) is difficult to complete, remove the unused import statements.

2053 'Solution' uses APIs that are not included in 'Import Statement'.

2054 Add the corresponding import statements if these APIs are necessary to complete the functionality. ↩

2055 Otherwise, refine 'Function Description' so that the functionality will require such APIs.

2056 'Solution' uses less than 2 libraries.

2057 You should refine 'Programming Problem' so that the functionality must require the API usage and invoke ↩

2058 APIs from at least 2 distinct libraries. You can use ChatGPT (GPT-4) in Advanced Data Analysis for ↩

2059 inspiration.

2060 'Solution' uses APIs in 'random' or the random functionality.

2061 Initialize the random seed for each 'TestCases' to control the behavior.

2062 'Solution' contains dummy code.

2063 Based on your understanding, replace the dummy code with the actual implementation of each part.

2064 'Solution' contains the display functionality, such as 'print()' and 'matplotlib.pyplot.show()'.

2065 If the function requires you to write or show some data, you shall either return the data or make the ↩

2066 function take a path for file storage or a variable for data visualization. For example, if the ↩

2067 function requires you to show a plot, you must return the plot (via Axes). If there is a specific ↩

2068 attribute inside the object, you should mention it in the 'Docstring' and test it inside 'TestCases'. ↩

2069 For example, the plot contains the specific title or label names. You should make sure that these ↩

2070 attributes are either stated in 'Docstring' or implied by 'Docstring'.

2071 If the function requires checking some properties and uses 'print()' to show the results, you need to ↩

2072 modify this function to return these results. The revised function should amalgamate these properties ↩

2073 with the preexisting return values, thereby facilitating more versatile utilization of the outputs ↩

2074 in the rest of your code.

2075 Refer to Step3 in the guidelines of the previous stage.

2076 Global constants before 'Problem Function'.

2077 If the global constants are used as sample inputs in the 'Solution', remove them and write your own test ↩

2078 input in 'TestCases'.

2079 If the global constants are unused, remove them directly.

2080 Test cases inside 'TestCases' only check the range of returned results or fail to test in a specific way.

2081

2052 It assumes that you now have full control of 'Programming Problem'. Write the test cases to validate if  
 2053 the returned results are equal to certain values. For the returned objects, validate if the  
 2054 attributes are equal to certain values.  
 2055 Test cases do not use any deterministic values as expected outputs.  
 2056 Come up with the expected outputs after testing.  
 2057 'TestCases' uses libraries or APIs that are not included in 'Import Statement'.  
 2058 Add the corresponding import statements if these APIs are necessary to complete the testing. Otherwise,  
 2059 remove such APIs.  
 2060 'TestCases' contains test cases that do not work for 'Solution'.  
 2061 Repair these test cases or replace them with better cases.  
 2062 'TestCases' does not test all attributes of the returned object, where these attributes are implied by  
 2063 'Function Description' or completed by 'Solution'.  
 2064 Add lines of code to test these attributes.  
 2065 If these attributes are not mentioned or implied by 'Function Description', try to describe them in  
 2066 'Function Description'.  
 2067 'TestCases' does not test the files that result in 'Solution'.  
 2068 Some files are created during the execution of 'Programming Problem'. Add necessary lines of code to test  
 2069 the attributes of these files in each test case.  
 2070 'TestCases' is wrapped in 'run\_tests'.  
 2071 Separate these two.  
 2072 Test cases in 'TestCases' are duplicated or used to test the same behavior.  
 2073 Remove them if there is a huge overlap. Replace them with more complex test cases. Make sure that at least  
 2074 five test cases are included.  
 2075 Test data used in 'TestCases' is missing.  
 2076 You need to manually design the data or utilize 3rd party libraries and websites (e.g. 'Faker' and  
 2077 'unittest.mock') to generate or mock the test data. Refer to Step4 in the guidelines of previous stage  
 2078 .  
 2079 Lack of return value.  
 2080 Functions should have clear return values to indicate the result, and these should be tested in the  
 2081 'TestCases'.  
 2082 Lack of corner cases.  
 2083 Corner cases should be considered in the function or in the test cases.  
 2084 Lack of error handling:  
 2085 You should add necessary checks for null inputs, incorrect data types, or values out of expected ranges to  
 2086 deal with incorrect input format.

2074 ## Further Explanation of Each Issue

- 2075 1. 'Function Name' has not been obfuscated:  
 2076 - The given function should have a generic name such as 'f' to ensure anonymity. This prevents the  
 2077 user from inferring the function's purpose based on its name.  
 2078 - Example:  
 2079 Before: 'def calculate\_average(nums):'  
 2080 After: 'def f(nums):'
- 2081 2. 'Docstring' is unclear, ambiguous, impractical or not well aligned with 'Solution':  
 2082 - The function's docstring should provide a clear and concise description of its purpose, expected  
 2083 inputs, outputs, and examples of usage. If the description is vague or doesn't match the function's  
 2084 behavior, it can lead to confusion.  
 2085 - Example:  
 2086 Before: '"""Calculates something."""'  
 2087 After: '"""Calculates the average of a list of numbers."""'
- 2088 3. 'Solution' does not use all imported libraries or APIs:  
 2089 - If libraries are imported but not used in the function, it indicates redundant code or a mismatch  
 2090 between the problem description and the solution.  
 2091 - Example:  
 2092 Before: 'import math' (but no usage of 'math' in the function)  
 2093 After: Remove 'import math' or ensure it's used in the function.
- 2094 4. 'Solution' uses APIs that are not included in 'Import Statement':  
 2095 - All external libraries or functions used in the solution should be imported at the beginning of the  
 2096 script to ensure the code runs without errors.  
 2097 - Example:  
 2098 If using 'sqrt' from 'math' library in the function, ensure 'from math import sqrt' is present at  
 2099 the beginning.
- 2100 5. 'Solution' does not use any library APIs:  
 2101 - The problem should be designed in a way that requires the usage of library APIs to solve it,  
 2102 ensuring the challenge of integrating external tools.  
 2103 - Example:  
 2104 If the problem is to calculate the square root, the solution should leverage the 'math.sqrt'  
 2105 function.
- 2106 6. 'Solution' uses APIs in 'random', but does not pass a random seed to 'Function Parameters':  
 2107 - When using random functionalities, for reproducibility, it's good practice to allow the user to set  
 2108 a seed.  
 2109 - Example:  
 2110 Before: 'random.randint(1,10)'  
 2111 After: 'random.seed(seed); random.randint(1,10)'
- 2112 7. 'Solution' contains dummy code:  
 2113 - Placeholder or dummy code should be replaced with actual implementation to ensure the function works  
 2114 as expected.  
 2115 - Example:  
 2116 Before: '# TODO: Implement this'  
 2117 After: Actual implementation of the required logic.
- 2118 8. Unused global constants before 'Problem Function':  
 2119 - Any constants or variables that are not used in the solution should be removed to clean up the code.

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9. 'TestCases' uses libraries or APIs that are not included in 'Import Statement':
  - Similar to the solution, all external libraries or functions used in the test cases should be imported. ←
10. 'TestCases' contains test cases that do not work for 'Solution':
  - All test cases should be aligned with the function's behavior to ensure they test the function correctly. ←
11. 'TestCases' does not test all attributes of the returned object:
  - If the function returns an object with multiple attributes or methods, the test cases should validate all of them to ensure complete coverage. For example, when plotting data on a graph, you might get an 'AxesSubplot' object in return. This object has various attributes, like the title, x-label, y-label, and the data points themselves. You should test all of these attributes if they are required in the functionality. ←
12. 'TestCases' does not test the files that result in 'Solution':
  - If the function creates or modifies files, the test cases should validate these files to ensure the function works as expected. ←
13. 'TestCases' is wrapped in 'run\_tests':
  - The test cases and the function to run them should be separated for clarity.
14. Test cases in 'TestCases' are duplicated or used to test the same behavior:
  - Redundant test cases should be removed to keep the test suite concise and focused.
15. Test data used in 'TestCases' is missing:
  - All required data for testing should be provided or generated to ensure the test cases can run without issues. ←

## J EVALUATION SETUP

### J.1 INFERENCE

We perform all the model inference on A100 GPUs, except for the closed ones. For the closed models, we rely on their official APIs provided in the documents.

### J.2 EXECUTION

We conduct the execution mainly on the Intel(R) Xeon(R) Gold 6150 CPU @ 2.70GHz, composed of 2 sockets, with 18 cores per socket.

### J.3 PROMPT TEMPLATE

---

Please provide a self-contained Python script that solves the following problem in a markdown code block:  
{prompt }

---

Figure 14: Prompt template for models supported by vLLM (Kwon et al., 2023).



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---

Please generate self-contained code to complete the following problem:  
{prompt }

---

Figure 15: Prompt template for OpenAI/DeepSeek APIs.

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---

Please generate self-contained code to solve the following problem in a Python markdown block:  
{prompt }

---

Figure 16: Prompt template for Mistral model APIs.

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Please generate self-contained code to complete the following problem wrapped in a Python markdown block:  
{prompt }

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Figure 17: Prompt template for Anthropic model APIs.

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## K DETAILED BENCHMARKING RESULTS AND ANALYSIS

### K.1 DETAILED RESULTS

Table 7: Evaluating LLMs on BigCodeBench-Complete. Due to the training flaws in StarCoder2 and Granite-Code, we additionally strip the trailing newlines for model inference.

| Model                                       | Size / Checkpoint | Greedy Decoding |            | Random Sampling |        |
|---------------------------------------------|-------------------|-----------------|------------|-----------------|--------|
|                                             |                   | Original        | Calibrated | Pass@1          | Pass@5 |
| <i>Instruction-tuned LLMs</i>               |                   |                 |            |                 |        |
| GPT-4o (OpenAI, 2024a)                      | 2024-05-13        | 0.602           | 0.611      | 0.557           | 0.711  |
| GPT-4-Turbo (OpenAI, 2024b)                 | 2024-04-09        | 0.582           | 0.582      | 0.563           | 0.699  |
| GPT-4 (Achiam et al., 2023)                 | 0613              | 0.484           | 0.572      | 0.407           | 0.682  |
| GPT-3.5-Turbo (OpenAI, 2023)                | 0125              | 0.506           | 0.506      | 0.504           | 0.657  |
| Claude-3 (Anthropic, 2024)                  | Opus              | 0.568           | 0.574      | —               | —      |
|                                             | Sonnet            | 0.534           | 0.538      | —               | —      |
|                                             | Haiku             | 0.486           | 0.501      | —               | —      |
| Mistral (AI, 2024a)                         | Large             | 0.379           | 0.383      | 0.365           | 0.539  |
|                                             | Small             | 0.390           | 0.413      | 0.398           | 0.601  |
| DeepSeek-Chat (DeepSeek-AI, 2024)           | V2                | 0.494           | 0.494      | 0.482           | 0.596  |
| DeepSeek-Coder-instruct (Guo et al., 2024)  | 33B               | 0.511           | 0.511      | 0.491           | 0.687  |
|                                             | 6.7B              | 0.432           | 0.438      | 0.426           | 0.624  |
|                                             | 1.3B              | 0.293           | 0.296      | 0.270           | 0.468  |
| CodeLlama-instruct (Roziere et al., 2023)   | 70B               | 0.489           | 0.496      | 0.429           | 0.681  |
|                                             | 34B               | 0.351           | 0.356      | 0.266           | 0.518  |
|                                             | 13B               | 0.297           | 0.317      | 0.247           | 0.470  |
|                                             | 7B                | 0.254           | 0.257      | 0.193           | 0.403  |
| Llama3-instruct (AI@Meta, 2024)             | 70B               | 0.539           | 0.545      | 0.522           | 0.650  |
|                                             | 8B                | 0.368           | 0.369      | 0.338           | 0.562  |
| Qwen2-Instruct (Bai et al., 2023)           | 72B               | 0.539           | 0.540      | 0.489           | 0.682  |
|                                             | 57B-A14B          | 0.465           | 0.468      | 0.399           | 0.648  |
|                                             | 7B                | 0.407           | 0.421      | 0.329           | 0.577  |
| CodeQwen1.5-Chat (Bai et al., 2023)         | 7B                | 0.437           | 0.443      | 0.408           | 0.632  |
| Qwen1.5-Chat (Bai et al., 2023)             | 110B              | 0.432           | 0.444      | 0.425           | 0.590  |
|                                             | 72B               | 0.398           | 0.403      | 0.373           | 0.569  |
|                                             | 32B               | 0.410           | 0.420      | 0.375           | 0.557  |
| Yi-1.5-Chat (Young et al., 2024)            | 34B               | 0.433           | 0.428      | 0.411           | 0.622  |
|                                             | 9B                | 0.422           | 0.424      | 0.379           | 0.601  |
|                                             | 6B                | 0.338           | 0.339      | 0.290           | 0.496  |
| Mixtral-instruct (AI, 2024c)                | 8x22B             | 0.496           | 0.502      | 0.458           | 0.677  |
| Magicoder-S-DS (Wei et al., 2023)           | 6.7B              | 0.475           | 0.476      | 0.424           | 0.643  |
| CodeGemma-instruct (Team et al., 2024)      | 7B                | 0.383           | 0.393      | 0.334           | 0.568  |
| StarCoder2-Instruct (BigCode, 2024)         | 15B               | 0.437           | 0.451      | 0.404           | 0.610  |
| Granite-Code-Instruct (Mishra et al., 2024) | 34B               | 0.438           | 0.444      | 0.399           | 0.613  |
|                                             | 20B               | 0.421           | 0.421      | 0.375           | 0.600  |
|                                             | 8B                | 0.392           | 0.397      | 0.367           | 0.581  |
|                                             | 3B                | 0.315           | 0.315      | 0.250           | 0.466  |
| <i>Base LLMs</i>                            |                   |                 |            |                 |        |
| CodeLlama (Roziere et al., 2023)            | 70B               | 0.443           | —          | 0.364           | 0.639  |
|                                             | 34B               | 0.371           | —          | 0.297           | 0.570  |
|                                             | 13B               | 0.320           | —          | 0.243           | 0.527  |
|                                             | 7B                | 0.287           | —          | 0.207           | 0.457  |
| Llama3-base (AI@Meta, 2024)                 | 70B               | 0.433           | —          | 0.375           | 0.625  |
|                                             | 8B                | 0.288           | —          | 0.223           | 0.466  |
| DeepSeek-Coder-base (Guo et al., 2024)      | 33B               | 0.466           | —          | 0.401           | 0.661  |
|                                             | 6.7B              | 0.418           | —          | 0.343           | 0.599  |
|                                             | 1.3B              | 0.223           | —          | 0.174           | 0.412  |
| CodeQwen1.5 (Bai et al., 2023)              | 7B                | 0.456           | —          | 0.411           | 0.650  |
| Yi-1.5 (Young et al., 2024)                 | 34B               | 0.400           | —          | 0.302           | 0.575  |
|                                             | 9B                | 0.355           | —          | 0.295           | 0.563  |
|                                             | 6B                | 0.274           | —          | 0.201           | 0.435  |
| Mixtral-base (AI, 2024b)                    | 8x22B             | 0.455           | —          | 0.355           | 0.633  |
| CodeGemma (Team et al., 2024)               | 7B                | 0.373           | —          | 0.295           | 0.557  |
|                                             | 2B                | 0.239           | —          | 0.153           | 0.375  |
| StarCoder2 (Lozhkov et al., 2024)           | 15B               | 0.383           | —          | 0.332           | 0.609  |
|                                             | 7B                | 0.285           | —          | 0.232           | 0.514  |
|                                             | 3B                | 0.214           | —          | 0.178           | 0.416  |
| Granite-Code (Mishra et al., 2024)          | 34B               | 0.385           | —          | 0.333           | 0.582  |
|                                             | 20B               | 0.258           | —          | 0.286           | 0.552  |
|                                             | 8B                | 0.356           | —          | 0.287           | 0.536  |
|                                             | 3B                | 0.202           | —          | 0.177           | 0.406  |

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Table 8: Evaluating instruction-tuned LLMs on BigCodeBench-Instruct. We report the results of greedy decoding, paired with calibrated results. To understand the performance difference between BigCodeBench-Complete and BigCodeBench-Instruct, we compute  $\Delta(NL2C - C2C)$  for each model. We do not include the results of Granite-Code-Instruct 8B & 3B as they constantly have empty outputs.

| Model                   | Size / Checkpoint | Greedy Decoding |            | $\Delta(NL2C - C2C)$ |            |
|-------------------------|-------------------|-----------------|------------|----------------------|------------|
|                         |                   | Original        | Calibrated | Original             | Calibrated |
| GPT-4o                  | 2024-05-13        | 0.499           | 0.511      | -0.103               | -0.100     |
| GPT-4-Turbo             | 2024-04-09        | 0.480           | 0.482      | -0.102               | -0.100     |
| GPT-4                   | 0613              | 0.459           | 0.460      | -0.025               | -0.112     |
| GPT-3.5-Turbo           | 0125              | 0.382           | 0.391      | -0.124               | -0.115     |
| Claude-3                | Opus              | 0.452           | 0.455      | -0.116               | -0.119     |
|                         | Sonnet            | 0.425           | 0.427      | -0.109               | -0.111     |
|                         | Haiku             | 0.392           | 0.394      | -0.094               | -0.107     |
| DeepSeek-Chat           | V2                | 0.404           | 0.404      | -0.090               | -0.090     |
| DeepSeek-Coder-instruct | 33B               | 0.418           | 0.420      | -0.093               | -0.091     |
|                         | 6.7B              | 0.353           | 0.355      | -0.079               | -0.083     |
|                         | 1.3B              | 0.227           | 0.228      | -0.066               | -0.068     |
| CodeLlama-instruct      | 70B               | 0.405           | 0.407      | -0.084               | -0.089     |
|                         | 34B               | 0.289           | 0.290      | -0.062               | -0.066     |
|                         | 13B               | 0.282           | 0.285      | -0.015               | -0.032     |
|                         | 7B                | 0.218           | 0.219      | -0.036               | -0.038     |
| Llama3-instruct         | 70B               | 0.432           | 0.436      | 0.107                | -0.109     |
|                         | 8B                | 0.317           | 0.319      | -0.051               | -0.050     |
| Qwen2-Instruct          | 72B               | 0.382           | 0.385      | -0.157               | -0.155     |
|                         | 57B-A14B          | 0.357           | 0.361      | -0.108               | -0.060     |
|                         | 7B                | 0.280           | 0.291      | -0.127               | -0.130     |
| CodeQwen1.5-Chat        | 7B                | 0.393           | 0.396      | -0.044               | -0.047     |
| Qwen1.5-Chat            | 110B              | 0.336           | 0.350      | -0.096               | -0.094     |
|                         | 72B               | 0.326           | 0.332      | -0.072               | -0.071     |
|                         | 32B               | 0.318           | 0.323      | -0.092               | -0.097     |
| Yi-1.5-Chat             | 34B               | 0.335           | 0.339      | -0.098               | -0.089     |
|                         | 9B                | 0.343           | 0.345      | -0.079               | -0.079     |
|                         | 6B                | 0.255           | 0.256      | -0.083               | -0.083     |
| Mistral                 | Large             | 0.296           | 0.300      | -0.083               | -0.083     |
|                         | Small             | 0.318           | 0.321      | -0.072               | -0.092     |
| Mixtral                 | 8x22B             | 0.404           | 0.406      | -0.092               | -0.096     |
| Magicoder-S-DS          | 6.7B              | 0.360           | 0.362      | -0.115               | -0.114     |
| CodeGemma-instruct      | 7B                | 0.321           | 0.323      | -0.062               | -0.070     |
| StarCoder2-Instruct     | 15B               | 0.367           | 0.376      | -0.070               | -0.075     |
| Granite-Code-Instruct   | 34B               | 0.358           | 0.361      | -0.080               | -0.083     |
|                         | 20B               | 0.337           | 0.340      | -0.084               | -0.081     |

## K.2 FURTHER ANALYSIS

**Bigger models yield better programming performance** The performance on BigCodeBench displays signs of scaling laws, where the models with more parameters generally solve more programming tasks. While the scaling laws hold for most instruction-tuned and base LLMs, Mistral-Large appears less capable than Mistral-Small on both BigCodeBench-Complete and BigCodeBench-Instruct, implying that Mistral-Large may be under-fitting. Our findings are consistent with (Yan et al., 2024).

**Closed LLMs perform better than open LLMs** We notice that most strong LLMs on BigCodeBench are non-permissive, led by the models from OpenAI and Anthropic. Among the open LLMs, the best model, Llama3-instruct-70B, slightly outperforms Claude-3-Sonnet and ranks 5th on both BigCodeBench-Complete and BigCodeBench-Instruct. The most permissive LLMs are relatively small and, hence, remain in a gap from the non-permissive ones.

**Jack of all trades, master of most** Figure 7 shows the top 5 for instruction-tuned ranked on BigCodeBench-Complete. Best overall base LLMs like Dpsk-Coder-Base-6.7B excel in most domains but still fall short in certain ones. We suggest that the domain-specific specialty will likely result from the training data.

### LLMs are better at computation, cryptography, and general domains

We further investigate the performance among different domains and find that models tend to be more capable of the tools in computation, cryptography, and general domains. On the other hand, models frequently fail when the tasks involve network tools. Therefore, we encourage the development of models specializing in such low-performing domains. A few examples of failures in the network domain can be found in Appendix L Examples 6, 7, and 8.

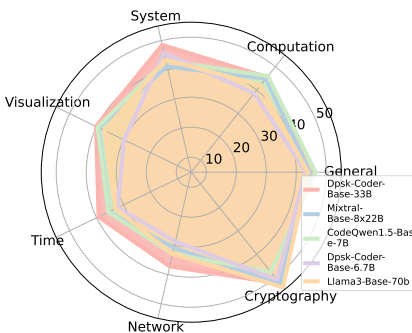


Figure 18: Top 5 base LLMs

## K.3 PROMPTING TECHNIQUES

Table 9: Calibrated Pass@1 comparison of plain prompting and zero-shot CoT prompting on both BigCodeBench and BigCodeBench-Hard.

| Split-Subset  | GPT-4o-2024-05-13 (%) | Gemini-1.5-Pro-API-0514 (%) |
|---------------|-----------------------|-----------------------------|
| Full-Complete | 61.1 → 59.4           | 57.5 → 55.9                 |
| Full-Instruct | 51.1 → 49.5           | 43.8 → 44.2 (↑)             |
| Hard-Complete | 29.1 → 34.5 (↑)       | 31.1 → 27.7                 |
| Hard-Instruct | 25.0 → 23.0           | 19.6 → 18.2                 |

We provide some preliminary studies on the effectiveness of the zero-shot chain-of-thought (CoT) (Kojima et al., 2022) on GPT-4o and Gemini-1.5-Pro by appending "\nLet's think step by step." to the end of the original prompt. From Table 9, we observe that there is no significant advantage to using zero-shot CoT for performing BigCodeBench tasks, indicating that the prompting technique is not sufficiently reliable for complex compositional reasoning. Therefore, we conclude that prompt design is very tricky and should not be recommended for the official evaluation setup. For our prompt design, we followed the same approach used in EvalPlus for consistency.

2376 L QUALITATIVE STUDIES  
2377

2378 Our benchmark exposes instances where even the strongest models struggle to use APIs, which may  
2379 not be exposed by simple benchmarks like HumanEval. Here, we show some examples with GPT-4o.  
2380

2381 **Example 1:** In the following example, the model fails to use `itertools.cycle` correctly,  
2382 producing an infinite loop.

```
2383 from collections import Counter
2384 import random
2385 from itertools import cycle
2386
2387 # Constants
2388 ELEMENTS = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J']
2389
2390 def task_func(l):
2391 """
2392 Create a counter from a list "l" and move the first 3 elements to the end of the list.
2393
2394 Parameters:
2395 - l (list): A list of elements that the function will process.
2396
2397 Returns:
2398 - counter (collections.Counter): A frequency counter that maps elements from the input list to their ←
2399 frequencies in the first 30 elements of the cycled, shuffled list.
2400
2401 Requirements:
2402 - collections
2403 - random
2404 - itertools
2405
2406 Example:
2407 >>> random.seed(42)
2408 >>> task_func(ELEMENTS)
2409 Counter({'I': 3, 'E': 3, 'G': 3, 'J': 3, 'E': 3, 'A': 3, 'B': 3, 'H': 3, 'D': 3, 'C': 3})
2410 """
2411 # Move the first 3 elements to the end of the list
2412 l = l[3:] + l[:3]
2413
2414 # Create a cycled, shuffled list
2415 cycled_list = list(cycle(l))
2416 ...
```

2404 **Example 2:** In this example, the model uses the semantics of `instanceof` incorrectly. Here,  
2405 `isinstance(j, (int, float))` does not actually check if `j` is an int or float, but rather the  
2406 type `(int, float)`.  
2407

```
2408 import pandas as pd
2409 import seaborn as sns
2410
2411 def task_func(data):
2412 """
2413 Analyze a dataset by calculating the average of values across each row and visualizing the correlation ←
2414 matrix as a heatmap.
2415
2416 Parameters:
2417 data (numpy.array): 2D array where each row represents a record and each column represents a feature
2418
2419 Returns:
2420 tuple: A tuple containing:
2421 - DataFrame: A pandas DataFrame enhanced with an 'Average' column that represents the mean across ←
2422 each row.
2423 - Axes: The matplotlib Axes object showing the heatmap of the correlations.
2424
2425 Requirements:
2426 - pandas
2427 - numpy
2428 - seaborn
2429
2430 Raises:
2431 ValueError: If the input data is not a 2D array or if it contains non-numeric data.
2432
2433 Example:
2434 >>> data = np.array([[1, 2, 3, 4, 5, 6, 7, 8], [8, 7, 6, 5, 4, 3, 2, 1]])
2435 >>> df, ax = task_func(data)
2436 >>> print(df['Average'].to_string(index=False))
2437 4.5
2438 4.5
2439 """
2440 # Check if data is a 2D array
2441 if not isinstance(data, (list, np.ndarray)) or not all(isinstance(i, (list, np.ndarray)) for i in data) ←
2442):
2443 raise ValueError("Input data is not a 2D array")
2444 # Check if data contains only numeric values
2445 if not all(all(isinstance(j, (int, float)) for j in i) for i in data):
```

```

2430
2431 raise ValueError("Input data contains non-numeric data")
2432 ...

```

**Example 3:** Here, the model mishandles the case where the directory does not exist with incorrect use of `os.path.dirname`.

```

2435 import pickle
2436 import os
2437 def task_func(filename, data):
2438 """
2439 Serialize an object using pickle and overwrite the specified file with this serialized data.
2440 Before writing, checks if the directory exists, creating it if necessary.
2441
2442 Parameters:
2443 - filename (str): The path of the file to be overwritten with serialized data.
2444 - data (object): The object to serialize and write to the file.
2445
2446 Returns:
2447 - bool: True if the operation is successful, False otherwise.
2448
2449 Requirements:
2450 - pickle
2451 - os
2452
2453 Example:
2454 >>> result = task_func('data.pkl', {'key': 'value'})
2455 >>> print(result)
2456 True
2457 """
2458 try:
2459 # Check if the directory exists
2460 dir_name = os.path.dirname(filename)
2461 if not os.path.exists(dir_name):
2462 # Create directory if it does not exist
2463 os.makedirs(dir_name)
2464
2465 # Open the file in write mode
2466 with open(filename, 'wb') as file:
2467 # Serialize the object and write it to the file
2468 pickle.dump(data, file)
2469
2470 return True
2471 except Exception as e:
2472 print(f"An error occurred: {e}")
2473 return False

```

**Example 4:** In this example, the model misunderstands how to use the `itertools.zip_longest` method. The arguments must be iterable, but the written function feeds single values.

```

2464 import numpy as np
2465 import itertools
2466 def task_func(data_list):
2467 """
2468 Unzips a list of tuples and calculates the mean of the numeric values for
2469 each position.
2470
2471 The function accepts a list of tuples, where each tuple consists of
2472 alphanumeric values. It unzips the tuples, and calculates the mean of
2473 numeric values at each position using numpy, where non numeric values are
2474 ignored. If all values at a position are non numeric, the mean at this
2475 position is set to be np.nan.
2476 If the provided tuples have different number of entries, missing values are
2477 treated as zeros.
2478
2479 Parameters:
2480 - data_list (list of tuples): The data to process, structured as a list of tuples. Each tuple can ←
2481 contain alphanumeric values.
2482
2483 Returns:
2484 - list: A list of mean values for each numeric position across the tuples. Non-numeric positions are ←
2485 ignored.
2486 An empty list is returned if the input list (data_list) is empty.
2487
2488 Requirements:
2489 - numpy
2490 - itertools
2491
2492 Example:
2493 >>> task_func([('a', 1, 2), ('b', 2, 3), ('c', 3, 4), ('d', 4, 5), ('e', 5, 6)])
2494 [nan, 3.0, 4.0]
2495 >>> task_func([(1, 'a', 2), ('a', 3, 5), ('c', 1, -2)])
2496 [1.0, 2.0, 1.6666666666666667]
2497 """
2498 if not data_list:

```

```

2484 return []
2485
2486 max_len = max(len(t) for t in data_list)
2487 data_list = [list(itertools.zip_longest(*t, fillvalue=0)) for t in data_list]
2488 ...

```

**Example 5:** In the following example, the model outputs code that has a different encoding for password\_hash and expected\_password\_hash so that even if the passwords are the same, the response will indicate a failed one.

```

2492 def task_func(data):
2493 """
2494 This method is designed to handle the authentication process in a web application context.
2495 It expects input in the form of a dictionary with 'username' and 'password' keys. The password
2496 is expected to be a base64-encoded SHA-256 hash. The method decodes and authenticates these
2497 credentials
2498 against predefined values (for demonstration purposes, it checks if the username is 'admin' and the
2499 password hash matches the hash of 'password'). Based on the authentication result, it returns an
2500 appropriate
2501 HTTP response.
2502
2503 Parameters:
2504 data (dict): A dictionary with 'username' and 'password' keys.
2505
2506 Returns:
2507 django.http.HttpResponse: An HttpResponse indicating the login result.
2508 HttpResponseBadRequest if the data is invalid.
2509
2510 Raises:
2511 KeyError, UnicodeDecodeError, binascii.Error, ValueError if the input dictionary is invalid.
2512
2513 Notes:
2514 - If the authentication success, the returned HttpResponse should contain 'Login successful.' with
2515 status 400.
2516 - If the authentication fails, the returned HttpResponse should contain 'Login failed.' with status
2517 401.
2518 - If the input data is invalid (i.e., password is a non-base64, missing keys), the function return
2519 HttpResponseBadRequest and it contains 'Bad Request.'
2520
2521 Examples:
2522 >>> from django.conf import settings
2523 >>> if not settings.configured:
2524 ... settings.configure()
2525 >>> data = {'username': 'admin', 'password': base64.b64encode(hashlib.sha256('password'.encode()).
2526 digest()).decode()}
2527 >>> response = task_func(data)
2528 >>> response.status_code == 200 and 'Login successful.' in response.content.decode()
2529 False
2530
2531 >>> data = {'username': 'admin', 'password': base64.b64encode(hashlib.sha256('wrongpassword'.encode()).
2532 digest()).decode()}
2533 >>> response = task_func(data)
2534 >>> response.status_code == 401 and 'Login failed.' in response.content.decode()
2535 False
2536
2537 Requirements:
2538 - django.http
2539 - django.conf
2540 - base64
2541 - hashlib
2542 - binascii
2543 """
2544 try:
2545 # Check if the required keys are present
2546 if 'username' not in data or 'password' not in data:
2547 raise KeyError('Missing keys in input data')
2548
2549 username = data['username']
2550 password_base64 = data['password']
2551
2552 # Decode the base64-encoded password
2553 try:
2554 password_hash = base64.b64decode(password_base64)
2555 except (binascii.Error, ValueError) as e:
2556 raise ValueError('Invalid base64 encoding')
2557
2558 # Predefined credentials for demonstration
2559 expected_username = 'admin'
2560 expected_password_hash = hashlib.sha256('password'.encode()).digest()
2561
2562 # Authenticate the credentials
2563 if username == expected_username and password_hash == expected_password_hash:
2564 return HttpResponse('Login successful.', status=200)
2565 else:
2566 return HttpResponse('Login failed.', status=401)
2567
2568 except (KeyError, UnicodeDecodeError, binascii.Error, ValueError) as e:
2569 return HttpResponseBadRequest('Bad Request.')

```

**Example 6:** This example showcases a failure to understand the nuances of the wikipedia library. When `page_title` is not found in Wikipedia, verbatim, the `wikipedia.page` method returns a `wikipedia.exceptions.DisambiguationError` rather than a `wikipedia.exceptions.PageError`.

```

2538
2539
2540
2541
2542
2543 import wikipedia
2544 from wordcloud import WordCloud
2545 import matplotlib.pyplot as plt
2546
2547 def task_func(page_title):
2548 """
2549 Create a word cloud from the text of a Wikipedia page.
2550
2551 Parameters:
2552 page_title (str): The title of the Wikipedia page.
2553
2554 Returns:
2555 matplotlib.axes.Axes: The Axes object of the plotted data. Is None if there is no wikipedia page with ←
2556 the title given as input.
2557
2558 Requirements:
2559 - wikipedia
2560 - wordcloud.WordCloud
2561 - matplotlib.pyplot
2562
2563 Example:
2564 >>> ax = task_func('Python (programming language)')
2565 """
2566 try:
2567 # Fetch the Wikipedia page content
2568 page_content = wikipedia.page(page_title).content
2569
2570 # Generate the word cloud
2571 wordcloud = WordCloud(width=800, height=400, background_color='white').generate(page_content)
2572
2573 # Plot the word cloud
2574 fig, ax = plt.subplots(figsize=(10, 5))
2575 ax.imshow(wordcloud, interpolation='bilinear')
2576 ax.axis('off') # Hide the axes
2577
2578 # Show the plot
2579 plt.show()
2580
2581 return ax
2582 except wikipedia.exceptions.PageError:
2583 # Return None if the page does not exist
2584 return None
2585
2586
2587
2588
2589
2590
2591

```

**Example 7:** In this *Network* example, the error actually originates from the regex. For the first example, instead of `www.google.com`, the regex actually extracts `www.google.com, ,` which leads to errors down the line.

```

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import re
import socket
import urllib.parse
def task_func(myString):
 """
 Extracts all URLs from a given string, analyzes each URL to extract the domain, and retrieves the IP ←
 address of each domain.
 Parameters:
 myString (str): The string from which URLs are extracted. The string should contain valid URLs ←
 starting with http or https.
 Returns:
 dict: A dictionary with domains as keys and their respective IP addresses (IPv4) as values. If a ←
 domain cannot be resolved, the IP address will be None.
 Requirements:
 - re
 - urllib.parse
 - socket
 Raises:
 socket.gaierror if the domain cannot be resolved
 Example:
 >>> task_func("Check these links: http://www.google.com, https://www.python.org")
 {'www.google.com': '172.217.12.142', 'www.python.org': '151.101.193.223'}
 """
 # Regular expression to find URLs
 url_pattern = re.compile(r'https?://[^\s/$.?#].[^\s]*')
 urls = url_pattern.findall(myString)
 # Dictionary to store domain and IP address
 domain_ip_map = {}

```



```

2592
2593 for url in urls:
2594 # Parse the URL to extract the domain
2595 parsed_url = urllib.parse.urlparse(url)
2596 domain = parsed_url.netloc
2597
2598 # Get the IP address of the domain
2599 try:
2600 ip_address = socket.gethostbyname(domain)
2601 except socket.gaierror:
2602 ip_address = None
2603
2604 # Add the domain and IP address to the dictionary
2605 domain_ip_map[domain] = ip_address
2606
2607 return domain_ip_map

```

**Example 8:** In this example, the model misunderstands the host naming structures. The issue is in the line `response = requests.get(f"https://ipinfo.io/ip_address/json")`, where the `/json` should not be present. This leads to a `hostname not found` error.

```

2606 import socket
2607 import requests
2608 def task_func(host):
2609 """
2610 This function resolves the IP address of the given host and then uses the IP address
2611 to fetch geolocation information from the ipinfo.io API. The function is robust against
2612 various common errors, such as invalid hostnames, network issues, or problems with the
2613 geolocation service.
2614
2615 Parameters:
2616 host (str): The hostname to be resolved.
2617
2618 Returns:
2619 dict: A dictionary containing the IP address and geolocation information if successful.
2620
2621 Raises:
2622 ValueError: If 'host' is None or an empty string.
2623 ConnectionError: If there is a problem connecting to the geolocation service.
2624
2625 Example:
2626 >>> result = task_func('google.com')
2627 >>> 'ip_address' in result and 'geolocation' in result
2628 True
2629 >>> task_func('')
2630 Traceback (most recent call last):
2631 ...
2632 ValueError: Host must be a non-empty string.
2633
2634 Requirements:
2635 - socket
2636 - requests
2637 """
2638 if not host:
2639 raise ValueError("Host must be a non-empty string.")
2640
2641 try:
2642 ip_address = socket.gethostbyname(host)
2643 except socket.gaierror:
2644 raise ValueError("Invalid hostname.")
2645
2646 try:
2647 response = requests.get(f"https://ipinfo.io/{ip_address}/json")
2648 response.raise_for_status()
2649 geolocation = response.json()
2650 except requests.RequestException as e:
2651 raise ConnectionError(f"Error connecting to the geolocation service: {e}")
2652
2653 return {
2654 "ip_address": ip_address,
2655 "geolocation": geolocation
2656 }

```

**Example 9:** This example shows an example where there is a simple solution using `flatten`, but the generated solution does not use this function and therefore gets the function incorrect.

```

2639 def task_func(dimension, seed=42):
2640 """
2641 Create a 2D numeric array (matrix) of a given dimension with random integers between 1 and 100,
2642 and a flat list of all elements in the matrix.
2643
2644 Parameters:
2645 - dimension (int): The dimension of the square matrix to be created. It must be a positive integer.
2646
2647 Returns:
2648 tuple: A tuple containing:
2649 - A 2D numpy array of the given dimension with random integers between 1 and 100.
2650 - A flat list of all elements in the matrix.

```

2646

2647

2648

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```

Requirements:
- numpy
- itertools

Example:
>>> matrix, flat_list = task_func(3)
>>> print(matrix)
[[52 93 15]
 [72 61 21]
 [83 87 75]]
>>> print(flat_list)
[52, 93, 15, 72, 61, 21, 83, 87, 75]
"""
Set the random seed for reproducibility
np.random.seed(seed)

Generate a 2D numpy array with random integers between 1 and 100
matrix = np.random.randint(1, 101, size=(dimension, dimension))

Flatten the matrix to a list
flat_list = list(itertools.chain.from_iterable(matrix))

return matrix, flat_list

Ground Truth
def task_func(dimension, seed=42):
 np.random.seed(seed) # Ensure reproducible results
 if dimension <= 0:
 raise ValueError("The dimension must be a positive integer")
 matrix = np.random.randint(1, 101, size=(dimension, dimension))
 flat_list = matrix.flatten().tolist()
 return matrix, flat_list

```

2667

2668

2669

**Example 10:** This is another example where the model chooses to use the wrong function. Here, it uses `np.mean` instead of `np.nanmean` (which the ground truth solution uses). This leads to the failure of a test with incomplete data.

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```

import pandas as pd
import numpy as np
import itertools
def task_func(data_list=[('a', 1, 2.1), ('b', 2, 3.2), ('c', 3, 4.3), ('d', 4, 5.4), ('e', 5, 6.5)]):
 """
 Calculate the mean of numerical values in each position across tuples in a list.
 Non-numeric values are ignored, and means are computed only from available data.
 That means that missing data in some of the tuples is simply ignored.

 A DataFrame with one columns named 'Mean Value' which contains the mean values for all tuple positions ←
 .
 The index is according to this scheme: 'Position i' where i is the current position.
 If an empty list is passed, then an empty DataFrame is returned.

 Parameters:
 data_list (list of tuples): A list containing tuples of mixed data types (string, int, float, etc.).
 Defaults to [('a', 1, 2.1), ('b', 2, 3.2), ('c', 3, 4.3), ('d', 4, 5.4), ('e', 5, 6.5)]

 Returns:
 DataFrame: A pandas DataFrame with the mean values of the numerical data at each position.

 Requirements:
 - pandas
 - numpy
 - itertools

 Example:
 >>> df = task_func()
 >>> print(df)
 Mean Value
 Position 0 NaN
 Position 1 3.0
 Position 2 4.3

 >>> data = [('a', '1', 2.1), ('b', 21, 'c'), (12, 3, 4.3), (['d'], 4, 5.4), ('e', 5, 6.5)]
 >>> df = task_func(data)
 >>> print(df)
 Mean Value
 Position 0 NaN
 Position 1 8.25
 Position 2 4.3
 """
 if not data_list:
 return pd.DataFrame(columns=['Mean Value'])

 # Transpose the list of tuples to get columns
 transposed = list(itertools.zip_longest(*data_list, fillvalue=np.nan))

 means = []
 for col in transposed:
 # Filter out non-numeric values
 numeric_values = [x for x in col if isinstance(x, (int, float))]

```

```

2700
2701 if numeric_values:
2702 mean_value = np.mean(numeric_values)
2703 else:
2704 mean_value = np.nan
2705 means.append(mean_value)
2706
2707 # Create the DataFrame
2708 index = [f'Position {i}' for i in range(len(means))]
2709 df = pd.DataFrame(means, index=index, columns=['Mean Value'])
2710
2711 return df
2712
2713 # Ground Truth Solution
2714 def task_func(data_list=[('a', 1, 2.1), ('b', 2, 3.2), ('c', 3, 4.3), ('d', 4, 5.4), ('e', 5, 6.5)]):
2715 unzipped_data = list(itertools.zip_longest(*data_list, fillvalue=np.nan))
2716 mean_values = []
2717 for column in unzipped_data[:]:
2718 numeric_values = [val for val in column if isinstance(val, (int, float))]
2719 if numeric_values:
2720 mean_values.append(np.nanmean(numeric_values))
2721 else:
2722 mean_values.append(np.nan)
2723 df = pd.DataFrame(mean_values, columns=['Mean Value'],
2724 index=[f'Position {i}'.format(i) for i in range(len(mean_values))])
2725 return df

```

## M UNIT TEST DESIGN

**HumanEval Test:** The HumanEval tests only consider input-output assertions, which only work for simple programs without configuration and environment setup. We use several tests below as an example.

```

2723 METADATA = { 'author': 'jt', 'dataset': 'test' }
2724
2725 def check(candidate):
2726 assert candidate([1.0, 2.0, 3.9, 4.0, 5.0, 2.2], 0.3) == True
2727 assert candidate([1.0, 2.0, 3.9, 4.0, 5.0, 2.2], 0.05) == False
2728 assert candidate([1.0, 2.0, 5.9, 4.0, 5.0], 0.95) == True
2729 assert candidate([1.0, 2.0, 5.9, 4.0, 5.0], 0.8) == False
2730 assert candidate([1.0, 2.0, 3.0, 4.0, 5.0, 2.0], 0.1) == True
2731 assert candidate([1.1, 2.2, 3.1, 4.1, 5.1], 1.0) == True
2732 assert candidate([1.1, 2.2, 3.1, 4.1, 5.1], 0.5) == False

```

**BigCodeBench Unit Test:** We demonstrate the design of BigCodeBench unit tests as follows, where we mock various scenarios for the network connection and validate the program behaviours. Compared to the ones in HumanEval and other benchmarks like APPS using input-output assertions, our unit tests require great human effort to design and cover various settings.

```

2734 # Requirements SetUp
2735 import unittest
2736 from unittest.mock import patch
2737 import http.client
2738 import ssl
2739 import socket
2740
2741 # Start the test
2742 class TestCases(unittest.TestCase):
2743
2744 # Mock the successful connection and assess the response content
2745 @patch('http.client.HTTPSConnection')
2746 def test_response_content(self, mock_conn):
2747 """ Test the content of the response. """
2748 mock_conn.return_value.getresponse.return_value.read.return_value = b'Expected Content'
2749 result = task_func('www.example.com', 443, '/content/path')
2750 self.assertEqual(result, 'Expected Content')
2751
2752 # Mock the failed connection and assess the error handling
2753 @patch('socket.create_connection')
2754 @patch('http.client.HTTPSConnection')
2755 def test_ssl_handshake_error_handling(self, mock_conn, mock_socket):
2756 """ Test handling of SSL handshake errors. """
2757 mock_socket.side_effect = ssl.SSLError('SSL handshake failed')
2758 with self.assertRaises(ssl.SSLError):
2759 task_func('badssl.com', 443, '/test/path')
2760
2761 # More test cases...

```

We further illustrate how the unit test is constructed for the programming tasks related to data visualization. In the following example, the function `task_func` returns both a DataFrame and a bar chart Axes object for validation. The DataFrame's Category and Value columns are

2754 tested to ensure they correctly represent the input data. The Axes object is validated for its title  
 2755 ("Category vs Value") and bar properties, including heights and x-axis labels, using a helper  
 2756 method, `is_bar`. The test cases cover diverse inputs with varying data sizes and values, ensuring  
 2757 the function reliably handles both data transformation and visualization requirements. We note that  
 2758 the test case design for the visualization tasks is similar to DS-1000 (Lai et al., 2023) but with more  
 2759 detailed validation.

```

2760 import pandas as pd
2761 import matplotlib.pyplot as plt
2762 import seaborn as sns

2763 def task_func(list_of_pairs):
2764 """
2765 Create a Pandas DataFrame from a list of pairs and visualize the data using a bar chart.
2766 - The title of the barplot should be set to 'Category vs Value'.
2767
2768 Parameters:
2769 list_of_pairs (list of tuple): Each tuple contains:
2770 - str: Category name.
2771 - int: Associated value.
2772
2773 Returns:
2774 tuple:
2775 - DataFrame: A pandas DataFrame with columns 'Category' and 'Value'.
2776 - Axes: A matplotlib Axes displaying a bar chart of categories vs. values.
2777
2778 Requirements:
2779 - pandas
2780 - matplotlib.pyplot
2781 - seaborn
2782
2783 Example:
2784 >>> list_of_pairs = [('Fruits', 5), ('Vegetables', 9)]
2785 >>> df, ax = task_func(list_of_pairs)
2786 >>> print(df)
2787 Category Value
2788 0 Fruits 5
2789 1 Vegetables 9
2790 """
2791 pass

2792 import unittest
2793 class TestCases(unittest.TestCase):
2794 """Test cases for the task_func function."""
2795 @staticmethod
2796 def is_bar(ax, expected_values, expected_categories):
2797 extracted_values = [
2798 bar.get_height() for bar in ax.patches
2799] # extract bar height
2800 extracted_categories = [
2801 tick.get_text() for tick in ax.get_xticklabels()
2802] # extract category label
2803 for actual_value, expected_value in zip(extracted_values, expected_values):
2804 assert (
2805 actual_value == expected_value
2806), f"Expected value '{expected_value}', but got '{actual_value}'"
2807 for actual_category, expected_category in zip(
2808 extracted_categories, expected_categories
2809):
2810 assert (
2811 actual_category == expected_category
2812), f"Expected category '{expected_category}', but got '{actual_category}'"
2813 def test_case_1(self):
2814 df, ax = task_func(
2815 [
2816 ("Allison", 49),
2817 ("Cassidy", 72),
2818 ("Jamie", -74),
2819 ("Randy", -25),
2820 ("Joshua", -85),
2821]
2822)
2823 # Testing the DataFrame
2824 self.assertEqual(
2825 df["Category"].tolist(), ["Allison", "Cassidy", "Jamie", "Randy", "Joshua"]
2826)
2827 self.assertEqual(df["Value"].tolist(), [49, 72, -74, -25, -85])
2828 # Testing the plot title
2829 self.assertEqual(ax.get_title(), "Category vs Value")
2830 self.is_bar(
2831 ax=ax,
2832 expected_categories=["Allison", "Cassidy", "Jamie", "Randy", "Joshua"],
2833 expected_values=[49, 72, -74, -25, -85],
2834)
2835
2836 # More test cases...

```

## N COMPARISON TO MORE PROGRAMMING BENCHMARKS

Table 10: Correlation coefficients measured by Pearson’s  $r$  and Spearman’s  $p$ , against MBPP+ and NaturalCodeBench.

|                  | BigCodeBench-Complete |       | BigCodeBench-Instruct |       |
|------------------|-----------------------|-------|-----------------------|-------|
|                  | $r$                   | $p$   | $r$                   | $p$   |
| MBPP+            | 0.963                 | 0.937 | 0.926                 | 0.881 |
| NaturalCodeBench | 0.757                 | 0.803 | 0.913                 | 0.857 |

We further compare model performances on BigCodeBench-Complete against existing benchmarks like MBPP+ (Liu et al., 2024) and NaturalCodeBench (Python-English) (Zhang et al., 2024) used for evaluating the coding capabilities of LLMs. We compute the Pearson and Spearman correlation coefficients for the calibrated model ranks on BigCodeBench-Complete and BigCodeBench-Instruct against HumanEval+ and NaturalCodeBench. From Table 10, MBPP+ is strongly correlated with BigCodeBench. The correlation between NaturalCodeBench and BigCodeBench-Complete is slightly lower, which is expected as NaturalCodeBench prompts are more similar to BigCodeBench-Instruct.

## O EVALUATION ON LESS-STRUCTURED INSTRUCTIONS

Although BigCodeBench-Instruct targets the conversational setup, the rule-based prompt structure may not fully reflect how the user prompts look. In real-world scenarios, the user prompts can be less structured and more ambiguous. For instance, in the following case shown in the first text block, the user may prompt the model differently, with a less-specified task description (as shown in the second block). The user no longer describes the title name and the return type. To simulate such cases, we preliminarily study several representative models on the rephrased BigCodeBench-Hard, where the NL part was rephrased by Llama-3.1-8B-Instruct. For the rephrasing prompt, we use “Please rephrase the following programming description in clear and concise plain text. Keep the core meaning intact but use different wording. Write in a casual style from a user’s perspective, without including any task completion markers.\n\n# Programming Description\n”. We set the temperature to 0.2 and top\_k as 0.95.

```

Train a random forest classifier to perform the classification of the rows in a dataframe with respect to
the column of interest plot the bar plot of feature importance of each column in the dataframe.
- The xlabel of the bar plot should be 'Feature Importance Score', the ylabel 'Features' and the title '
Visualizing Important Features'.
- Sort the feature importances in a descending order.
- Use the feature importances on the x-axis and the feature names on the y-axis.
The function should output with:
sklearn.model.RandomForestClassifier : The random forest classifier trained on the input data.
matplotlib.axes.Axes: The Axes object of the plotted data.
You should write self-contained code starting with:

'''
from sklearn.ensemble import RandomForestClassifier
import seaborn as sns
import matplotlib.pyplot as plt
def task_func(df, target_column):
'''

```

```

I want to use a random forest classifier to predict the class of each row in a dataset based on a specific
column. I also want to create a bar chart that shows how important each feature is in making those
predictions. The chart should have a title, labels for the x and y axes, and the features should be
listed on the y-axis in order of how important they are. The output should include the trained random
forest classifier and the chart itself. Please start with:

'''
from sklearn.ensemble import RandomForestClassifier
import seaborn as sns
import matplotlib.pyplot as plt
def task_func(df, target_column):
'''

```

From Table 11, it is evident that Qwen2.5-Coder-32B-Instruct exhibits a more significant performance drop compared to other models, despite its stronger performance on the original BigCodeBench-Hard. While it is true that rephrased instructions may introduce additional ambiguity, the results indicate that some models may still lack sufficient robustness to handle less structured and more casual inputs.

2862 Table 11: Performance comparison across models for original BigCodeBench-Instruct  
 2863 (**Original**), rephrased, and the differences.

| 2864 | 2865                       | 2866            | 2867             | 2868       | 2869 | 2870 |
|------|----------------------------|-----------------|------------------|------------|------|------|
|      | <b>Original Model</b>      | <b>Original</b> | <b>Rephrased</b> | $\Delta$ ↓ |      |      |
|      | Qwen2.5-Coder-32B-Instruct | 27.7            | 8.8              | -18.9      |      |      |
|      | Llama-3.1-70B-Instruct     | 23.6            | 11.5             | -12.1      |      |      |
|      | GPT-4o-mini-2024-07-18     | 23.6            | 10.1             | -13.5      |      |      |
|      | GPT-4o-2024-05-13          | 25.0            | 12.8             | -12.2      |      |      |

2871  
 2872 This highlights a potential area for future improvement in LLM capabilities, particularly in managing  
 2873 variations in natural language.

## 2874 P BIGCODEBENCH: EVALUATION INFRASTRUCTURE

2875  
 2876 In this section, we document the usage of `bigcodebench`, the evaluation infrastructure for  
 2877 BigCodeBench. We note that the prototype of `bigcodebench` is based on EvalPlus (Liu  
 2878 et al., 2024).

```
2881 bigcodebench.evaluate \

 2882 --model meta-llama/Meta-Llama-3.1-8B-Instruct \

 2883 --split [complete|instruct] \

 2884 --subset [full|hard] \

 2885 --backend [vllm|openai|anthropic|google|mistral|hf]
```

```
2886 bigcodebench.inspect --dataset [bigcodebench] --eval-results samples-sanitized_eval_results.json [--in-

 2887 place]
```

## 2888 Q DEVELOPMENT TIMELINE

2889 **04/2023 - 05/2023** Project Initiation.

2890  
 2891 **06/2023 - 07/2023** Benchmark Construction — Data Synthesis.

2892  
 2893 **07/2023 - 11/2023** Benchmark Construction — Semi-automatic Program Refactoring and Testing  
 2894 Case Generation.

2895  
 2896 **12/2023 - 04/2024** Benchmark Construction — Human Curation; BigCodeBench Evaluation  
 2897 Tool Development.

2898  
 2899 **04/2024 - 05/2024** Benchmark Finalization; Experiment; Analysis; Drafting; Code-Eval Develop-  
 2900 ment.

2901  
 2902 **06/2024** Initial BigCodeBench Release.