
Top Leaderboard Ranking = Top Coding Proficiency, Always?

 **EVOEVAL: Evolving Coding Benchmarks via LLM**

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Abstract

LLMs have become the go-to choice for code generation tasks, with an exponential increase in the training, development, and usage of LLMs specifically for code generation. To evaluate the ability of LLMs on code, both academic and industry practitioners rely on popular handcrafted benchmarks. However, prior benchmarks contain only a very limited set of problems, both in quantity and variety. Further, due to popularity and age, many benchmarks are prone to data leakage where example solutions can be readily found on the web and thus potentially in training data. Such limitations inevitably lead us to inquire: *Is the leaderboard performance on existing benchmarks reliable and comprehensive enough to measure the program synthesis ability of LLMs?* To address this, we introduce  EVOEVAL— a program synthesis benchmark suite created by *evolving* existing benchmarks into different targeted domains for a comprehensive evaluation of LLM coding abilities. Our study on 51 LLMs shows that compared to the high performance obtained on standard benchmarks like HUMANEVAL, there is a significant drop in performance (on average 39.4%) when using EVOEVAL. Additionally, the decrease in performance can range from 19.6% to 47.7%, leading to drastic ranking changes amongst LLMs and showing potential overfitting of existing benchmarks. Furthermore, we showcase various insights, including the brittleness of instruction-following models when encountering rewording or subtle changes as well as the importance of learning problem composition and decomposition. EVOEVAL not only provides comprehensive benchmarks, but can be used to further evolve arbitrary problems to keep up with advances and the ever-changing landscape of LLMs for code. We have open-sourced our benchmarks, tools, and complete LLM generations at <https://github.com/evo-eval/evoeval>

1 Introduction

Program synthesis [15] is widely regarded as the *holy-grail* in the field of computer science. Recently, large language models (LLMs) have become the default choice for program synthesis due to its code reasoning capabilities acquired through training on large amounts of open-source code repositories. Popular LLMs like GPT-4 [36], Claude-3 [3], and Gemini [43] have shown tremendous success in aiding developers on a wide-range of coding tasks such as code completion [10], repair [51], and test generation [12]. Furthermore, researchers and industry practitioners have designed code LLMs (e.g., DeepSeeker Coder [16], CodeLlama [40], and StarCoder [26]) using a variety of training methods designed specifically for the code domain to improve LLM code understanding.

In order to evaluate the coding abilities of LLMs, benchmarks like HUMANEVAL [10] and MBPP [4] have been handcrafted to evaluate the program synthesis task of turning natural language descriptions (e.g., docstrings) into code snippets. These code benchmarks measure

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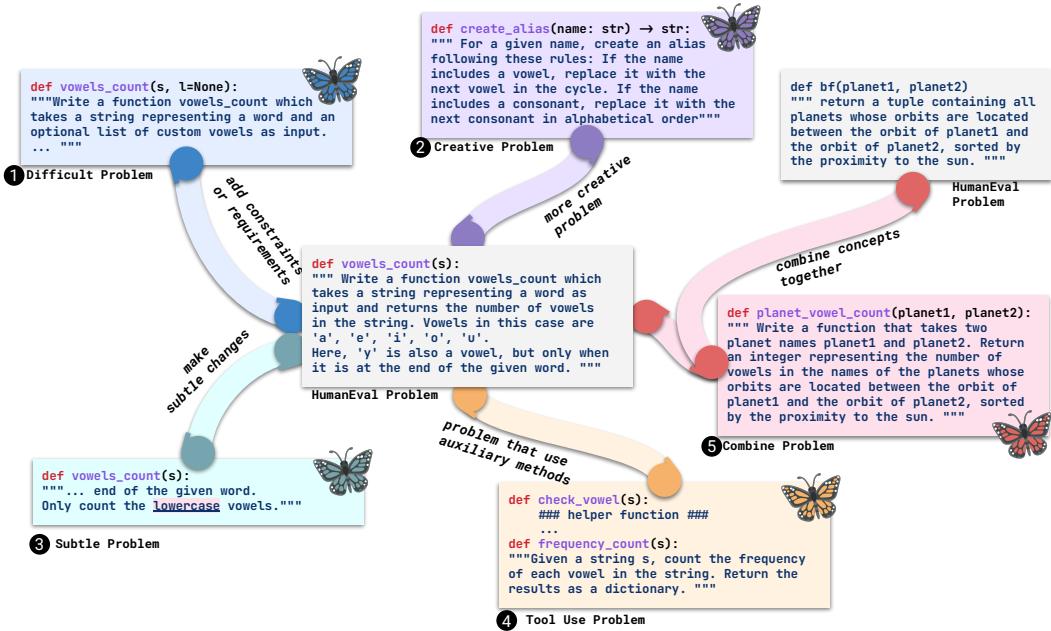


Figure 1: Example problems generated in EVOEVAL through the use of targeted transformation prompts starting from a HUMANEVAL problem.

functional correctness by evaluating LLM-generated solutions against a set of limited predefined tests. Recent work [28] has further improved these benchmarks with augmented tests to rigorously evaluate the functional correctness of LLM generated code. However, apart from test inadequacy, existing popular code synthesis benchmarks have the following limitations:

- **Limited amount and variety of problems.** Code benchmarks are mainly constructed by human annotators manually. Due to the high manual effort required, they only contain a limited amount of problems. For example, HUMANEVAL [10] only contains 164 hand-crafted problems. Such a low amount of problems is not sufficient to fully measure the complete spectrum of program synthesis capability of state-of-the-art LLMs. Additionally, these code benchmarks include mostly self-contained coding problems that lack variety in both problem types and domains, where the final evaluation output only shows the percentage of problems solved. While they provide a baseline overview of the coding abilities, LLM builders and users cannot gain deeper insights to exactly what problem types or coding scenarios the particular LLM may excel or struggle in.
- **Prone to data leakage and training dataset composition.** Popular benchmarks like HUMANEVAL and MBPP were released almost 4 years ago, with example solutions available in third-party open-source repositories. While recent LLMs have been taking turns climbing the leaderboard by achieving higher pass@1 scores (often with less than 1 percent difference between the next best model), just how much of that is attributed to having leaked solutions as part of the training data? Furthermore, the problems within these benchmarks are often simple derivatives of common coding problems/concepts. In fact, recent work [39] has shown that there are substantial overlap between benchmark solutions and open-source training corpuses. In addition, closed-source LLMs may even deliberately include benchmark groundtruths to artificially boost their leaderboard status [7]. As such, it is unclear whether high scores achieved by LLMs are truly due to their learnt coding capability or instead obtained via memorizing benchmark solutions.

As more LLMs are being constructed, trained, and used especially for code, the insufficient evaluation benchmarks raise the question of validity: *Is leaderboard performance on existing benchmarks reliable and comprehensive enough to measure the program synthesis ability of LLMs?*

Our work. To address the limitation of existing benchmarks, we introduce  EVOEVAL¹ – a set of program synthesis benchmarks created by *evolving* existing problems. The key idea behind EVOEVAL is to use LLMs instead of humans to produce new code synthesis problems based on a variety of different instructions aimed at evolving or transforming the existing benchmark problems into targeted domains for more comprehensive evaluation. Different from prior benchmark constructions that either obtain problems from open-source repositories or databases – leading to data leakage or require manual construction of each problem – resulting in high manual effort and limited diversity, EVOEVAL directly uses LLMs with targeted transformation prompts to synthesize new coding problems. Specifically, we design 5 different targeted transformation prompts: *Difficult*, *Creative*, *Subtle*, *Combine* and *Tool Use*. We then prompt GPT-4 to independently transform any existing problem in previous benchmarks into a new problem in the targeted domain.

Figure 1 shows a concrete example of EVOEVAL in action starting with an initial problem in HUMANEVAL– `vowel_counts` to count the number of vowels in the string. ① We first observe the transformation to a more difficult problem by asking GPT-4 to add additional constraints or requirements. This new problem contains a separate custom vowel list that makes the overall program logic more complex. ② We can also transform to a more creative problem of `create_alias` that still uses concepts like vowels and consonants but involves a much more creative and unusual problem description. ③ We can also make subtle changes to the problem where we only count the lowercase vowels to test if the LLM is simply memorizing the benchmark. ④ We can additionally combine concepts from multiple problems together. In the example, we use another problem `bf` to create a new problem that returns the vowels in each planet sorted based on the orbiting order. ⑤ Furthermore, we can test the ability for LLMs to utilize auxiliary helper functions (common place in real-world code repositories) to solve more complex problems. Again we reuse the concepts of vowels from the initial problem, where the frequency of each vowel should be computed. However instead of directly solving the problem, the LLM can directly use the provided `check_vowel` helper function to simplify the solution.

Together, each of these transformed benchmarks are designed to introduce more difficult and complex problems as well as test different aspects of the LLM code understanding and synthesis ability. In EVOEVAL, we additionally use GPT-4 to generate the groundtruth solution to each problem as well as rigorous test cases to ensure we can evaluate the functional correctness of LLM-synthesized code on EVOEVAL. Finally, we manually check each generated problem and corresponding groundtruth to ensure problem clarity and correctness. EVOEVAL serves as a way to further evolve existing benchmarks into more complex and well-suited problems for evaluation in order to keep up with the ever-growing LLM research.

Contribution. Our work proposes to evolve existing problems for benchmark creation:

- **Benchmark:** We present EVOEVAL– a set of program synthesis benchmarks created by evolving existing popular HUMANEVAL coding benchmark problems. EVOEVAL includes 828 problems across 5 semantic-altering and 2 semantic-preserving benchmarks. Furthermore, EVOEVAL also includes additional benchmarks to study program synthesis concepts like problem composition and decomposition. EVOEVAL is fully complete with groundtruth implementations and robust testcases to evaluate functional correctness.
- **Approach:** We propose a complete pipeline to directly synthesize new coding problems for benchmarking by evolving existing problems through the use of targeted transformation prompts. Our pipeline aims to reduce manual checking effort using a self-consistency approach to automatically refine any problem inconsistencies and generate groundtruth as well as test cases. Our approach is general and can be used on other benchmark problems, adopted for transformation into additional domains or utilize different problem generation strategies [50].
- **Study:** We conduct a comprehensive study on 51 different LLMs across all benchmarks in EVOEVAL. We found that compared to the high performance obtained on standard benchmarks like HUMANEVAL, when evaluated on EVOEVAL, popular LLMs significantly drop in performance (on average 39.4%). Additionally, this drop is not uniform across all

¹coincidentally similar pronunciation with EVILEVAL

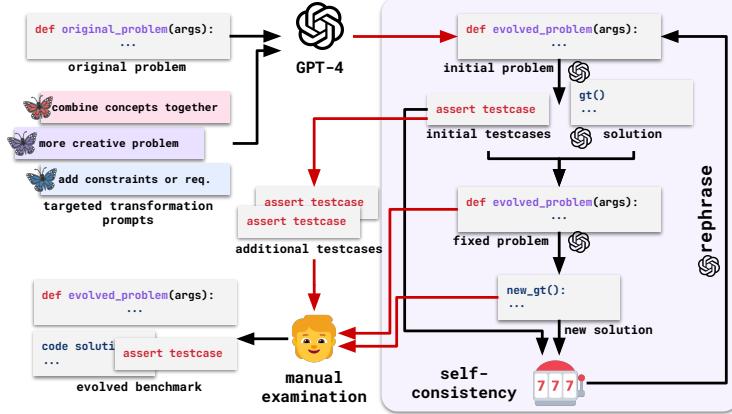


Figure 2: Overview of EVOEVAL evolving problem generation pipeline.

LLMs and can range from 19.6% to 47.7%, leading to drastic ranking changes amongst top performing models. We further demonstrate that certain LLMs cannot keep up their high performance obtained in HUMANEVAL when evaluated on more challenging or problems in different domains, highlighting the possibilities of overfitting to existing benchmarks. Moreover, we observe that while instruction-following LLMs perform well in solving self-contained problems, they struggle with the tool using aspect of utilizing already provided auxiliary functions. Furthermore, they are particularly sensitive to the problem description where rephrasing or subtle changes to the problem docstring leads to degradation in output solutions compared to their base non-instruction-following counterparts. Additionally, we demonstrate that current state-of-the-art LLMs fail to effectively compose multiple general coding concepts to solve more complex variants, or address subproblems decomposed from previously solved difficult problem.

2 Approach

Figure 2 shows the overview of the benchmark creation pipeline for EVOEVAL. We start by taking the original problem and apply a chosen targeted transformation prompt aimed at prompting GPT-4 to produce a new code synthesis problem along the targeted domain. Using this initial transformed problem, we enter our refinement pipeline to fix any ambiguities or inconsistencies in the problem description, as well as generating the test cases and groundtruth solution for functional evaluation. Finally, to ensure correctness, we manually examine each produced problem along with the groundtruth and make corresponding changes to produce the final evolved benchmarks.

Targeted problem transformation. EVOEVAL uses zero-shot prompting to evolve an existing coding benchmark to produce new and diverse problems. Each transformation prompt, as shown in the examples in Figure 1, aims to transform the existing problem in a specific manner. In particular, we define two different types of transformation prompts: 1) **semantic-altering** – change the semantic meaning of the original problem and 2) **semantic-preserving** – modify the problem description while keeping the semantic meaning the same. While Figure 1 shows only semantic-altering transformation prompts to produce new problems, we can also produce semantic-preserving problems to test additional aspect of the LLM coding abilities.

Problem refinement & groundtruth Generation. The initial evolved problem produced by GPT-4 may include small inconsistencies such as contradicting sentences or incorrect I/O examples in the docstring. For coding benchmarks, such inconsistencies are especially damaging as it can detract from the problem specification, leading to inaccurate evaluation of LLM coding capabilities. As such, we introduce a refinement pipeline to iteratively rephrase and refine problem as needed. In addition, during this process, we also use GPT-4

Table 1: EVOEVAL and HUMANEVAL benchmark statistics. Note: the number in bracket shows the number of testcases in the augmented HUMANEVAL+ benchmarks, in EVOEVAL, they are directly reused in SUBTLE, VERBOSE and CONCISE due the similarity.

	original		semantic-altering				semantic-preserving	
	HUMANEVAL	DIFFICULT	CREATIVE	SUBTLE	COMBINE	TOOL_USE	VERBOSE	CONCISE
# problems	164	100	100	100	100	100	164	164
Avg. problem len.	450.6	749.4	982.1	406.8	860.4	1224.6	450.6	450.6
Avg. # test cases	9.6 (764.1)	49.8	43.1	10.3 (745.4)	51.8	51.3	9.6 (764.1)	9.6 (764.1)

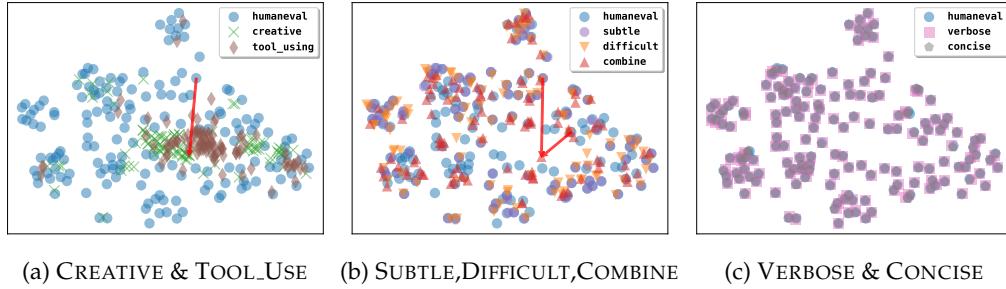


Figure 3: 2 dimensional t-SNE visualization of EVOEVAL benchmarks.

to produce the necessary groundtruth implementation of the function as well as example test cases to be used for evaluation.

We first directly use GPT-4 to obtain a possible solution for the initial problem. Additionally, we also prompt GPT-4 to extract (if available in the initial problem docstring) or produce the test inputs for the transformed problem. We then evaluate the test inputs on the solution to derive the corresponding expected test outputs. Next, using these test inputs/outputs, we instruct GPT-4 to add or fix the example test cases in the docstring, providing further demonstrations of the task.

Using this refined problem, we again generate a solution. We then leverage self-consistency [47] to check if the new solution on the test inputs produce the same outputs as the previous solution. The intuition is that since both solutions are generated by GPT-4 and the refined problem should only include minimal changes (e.g., adding new testcase examples), the solution output should then be the same in the absence of any potential inconsistencies or ambiguity in problem description. As such, if we observe differences between the two solution outputs, we ask GPT-4 to further rephrase and fix any inconsistencies in the original problem and repeat the process. On the other hand, if both solutions agree on outputs, we terminate the problem refinement stage and return the trio comprising of the new problem description, the solution as the groundtruth and the test cases for functional evaluation.

Manual examination & test augmentation. For each transformed problem, we carefully examine and adjust any final faults to ensure each problem and groundtruth is correctly specified and implemented. Additionally, using the initial set of test cases from the refinement stage, we further generate additional tests following the LLM-based test augmentation technique in EVALPLUS [28]. Finally, we produce EVOEVAL, a comprehensive code synthesis benchmark suite, which through the use of evolving transformations can generate diverse coding problems to evaluate LLM coding capability across various problem domains.

3 EVOEVAL Dataset Overview

We use the problems in HUMANEVAL as seeds to produce EVOEVAL. Problems in EVOEVAL consist mainly of self-contained functions, except for TOOL_USE that includes helper functions specifically designed to test the tool using capability of LLMs. Each problem uses a

docstring to illustrate the problem specification, along with test cases and groundtruth to evaluate the functional correctness. Table 1 shows the statistics of the benchmarks in EVOEVAL. In total, EVOEVAL includes 828 problems across 7 different datasets (5 semantic-altering and 2 semantic-preserving):

- **DIFFICULT:** Introduce complexity by adding additional constraints and requirements, replace commonly used requirements to less common ones, or add additional reasoning steps to the original problem.
- **CREATIVE:** Generate a more creative problem compared to the original through the use of stories or uncommon narratives.
- **SUBTLE:** Make a subtle and minor change to the original problem such as inverting or replacing a requirement.
- **COMBINE:** Combine two different problems by integrating the concepts from both problems. In order to select problems that make sense to combine, we apply a simple heuristic to combine only problems of the same type together categorized based on the type of input arguments in the original problem.
- **TOOL_USE:** Produce a new problem containing a main problem and one or more helpers functions which can be used to solve it. Each helper function is fully implemented and provides hints or useful functionality for solving the main problem. The main problem does not explicitly reference individual helper functions, and we do not require the model to use the provided helpers.
- **VERBOSE:** Rework the original docstring to be more verbose. These verbose docstrings can use more descriptive language to illustrate the problem, include detailed explanation of the example output, and provide additional hints.
- **CONCISE:** Rework the original docstring to be more concise by removing unnecessary details and using concise language. Furthermore, simple examples that are not required to demonstrate edge cases may be removed.

For each of the semantic-altering benchmarks, we generate 100 problems each using different seed problems from HUMANEVAL. For semantic-preserving benchmarks, we generate using all 164 problems in HUMANEVAL as it requires less validation since we can reuse the original groundtruths. As shown in Table 1, compared to HUMANEVAL, EVOEVAL contains longer coding questions with longer average problem length. Furthermore, EVOEVAL also uses more test cases to perform robust evaluation compared to base HUMANEVAL.

Figure 3 shows the embedding visualization using t-SNE [18]² by projecting high-dimension representation of the problems docstrings in both EVOEVAL and HUMANEVAL into the 2D plane. First, we see that CREATIVE and TOOL_USE drastically change the embedding distribution compared to the original dataset. The arrow in Figure 3a shows one example of the shift in distribution from the original problem to a creative one. Next, we see that SUBTLE, DIFFICULT and COMBINE largely retain the same distribution as the original problems. This is due to the high parity across these problem descriptions where SUBTLE only applies subtle changes and DIFFICULT adds additional complex constraints while keeping the main problem descriptions largely the same. Specifically, for COMBINE, we can see from an example arrow in Figure 3b, the new combined problem shifts the embedding for both of the original problems. Finally, we observe that for VERBOSE and CONCISE, the embeddings almost perfectly match the original problem, reflecting their semantic-preserving nature. In Appendix C, we present example problems for each benchmark in EVOEVAL.

4 Methodology

Setup. Each LLM generated sample is executed against the test cases in EVOEVAL and evaluated using differential testing [31] – comparing against the groundtruth results to measure functional correctness. We report the functional correctness by using the popular pass@ k metric. We focus on greedy decoding (i.e., producing a deterministic sample per each problem with temperature = 0). We denote this as pass@1.

²perplexity=50 and iter=1000 using text-embedding-3-large model from OpenAI

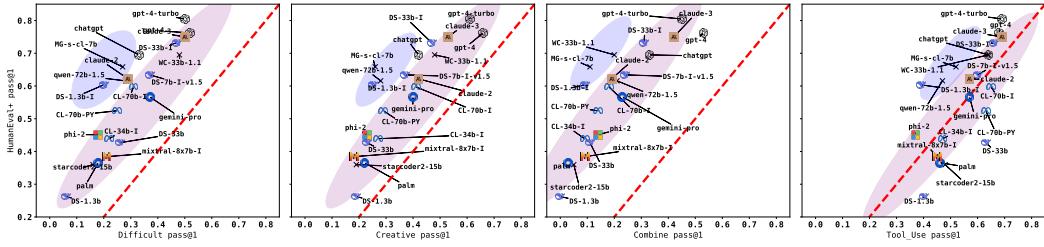


Figure 4: Comparison of pass@1 on HUMAN-EVAL+ and EVO-EVAL datasets of selected models. The red dotted identity line (i.e., $x = y$) represents equivalent performance on both HUMAN-EVAL and EVO-EVAL. For each benchmark, we cluster the LLMs into 1) purple region – aligned performance on HUMAN-EVAL and EVO-EVAL and 2) blue region – over performant LLMs on HUMAN-EVAL compared with EVO-EVAL results.

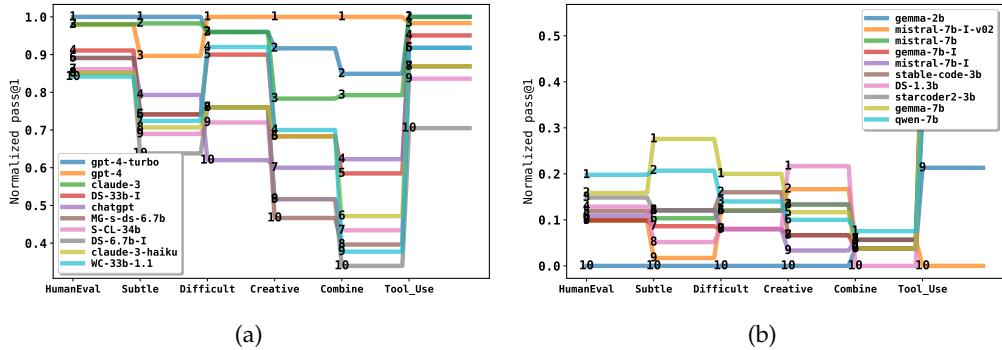


Figure 5: Ranking changes across EVO-EVAL benchmarks of (a) top-10 and (b) bottom-10 best performing LLMs on HUMAN-EVAL respectively. Y-axis shows the normalized pass@1 score defined as the LLM pass@1 normalized by the minimal and maximum pass@1 achieved by all LLMs on benchmark.

Models. We evaluate 51 popular state-of-the-art LLMs, including both proprietary and open-source models on EVO-EVAL. We evaluate not only the popular general-purpose LLMs but also include recent code-based LLMs for comprehensive evaluation. Further, we classify the LLMs as either base or instruction-following and focus our analysis on discussing the effect of model variants have on EVO-EVAL performance.

Input format. To produce the code solution using each LLM, we provide a specific input prompt: For base LLMs (i.e., not instruction-tuned variants), we simply use only the function header with the docstring and let the LLM autocomplete the solution. For instruction-following LLMs, we follow the model-makers’ guide on the exact instruction and format to use and ask the LLM to generate a complete solution for the problem.

5 Evaluation

5.1 LLM Synthesis & Evaluation on EVO-EVAL

EVO-EVAL produces more complex and challenging benchmarks for program synthesis. Table 2 shows the pass@1 performance along with the ranking of LLMs on each of the semantic-altering EVO-EVAL benchmarks with the average pass@1 and ranking on all benchmarks in the last columns. First, compared to the success rate on HUMAN-EVAL, when evaluated on EVO-EVAL, all LLMs **consistently perform worse**. For example, the state-of-the-art GPT-4, GPT-4-Turbo and Claude-3 models solve close to 85% of all HUMAN-EVAL problems but fall almost below 50% pass@1 when evaluated on the DIFFICULT problems. On average, across all benchmarks, the performance of LLMs decreased by 39.4%

Table 2: pass@1 and ranking results (* indicates tie) on the semantically-altering EVOEVAL and HUMANEVAL benchmarks. Note: 🤖 denotes instruction-following LLMs.

Size	HUMAN EVAL		DIFFICULT		CREATIVE		SUBTLE		COMBINE		TOOL USE		EVO EVAL		
	pass@1	rank	pass@1	rank	pass@1	rank	pass@1	rank	pass@1	rank	pass@1	rank	pass@1	rank	
GPT-4-Turbo	NA	83.5 (80.5)	1	50.0	*2	61.0	2	82.0	1	45.0	2	69.0	*1	65.1	2
GPT-4	NA	82.3 (76.2)	*2	52.0	1	66.0	1	76.0	3	53.0	1	68.0	3	66.2	1
ChatGPT	NA	76.8 (69.5)	*5	33.0	*13	42.0	*7	70.0	4	33.0	4	64.0	*6	53.1	6
Claude-3	NA	82.3 (75.0)	*2	50.0	*2	53.0	3	81.0	2	42.0	3	69.0	*1	62.9	3
Claude-3-haiku	NA	74.4 (66.5)	*8	40.0	*6	47.0	*5	65.0	*10	25.0	*6	61.0	*10	52.1	7
Claude-2	NA	66.5 (62.2)	*18	29.0	17	42.0	*7	64.0	*13	19.0	14	57.0	*16	46.2	15
Gemini	NA	62.2 (56.7)	21	37.0	*10	40.0	12	53.0	*21	23.0	*9	57.0	*16	45.4	17
PaLM-2	NA	40.2 (36.6)	38	18.0	*32	22.0	33	36.0	*42	3.0	*39	46.0	*29	27.5	37
DeepSeeker-Inst	33b	78.0 (73.2)	4	47.0	5	47.0	*5	67.0	*5	31.0	5	66.0	4	56.0	4
DeepSeeker	6.7b	74.4 (69.5)	*8	40.0	*6	37.0	*13	61.0	*17	18.0	*15	51.0	24	46.9	14
	1.3b	63.4 (60.4)	20	20.0	*30	25.0	*25	53.0	*21	9.0	*28	39.0	*41	34.9	24
DeepSeeker	33b	50.6 (42.7)	26	26.0	20	23.0	*30	47.0	*26	11.0	*25	63.0	*8	36.8	23
	6.7b	45.1 (38.4)	*31	21.0	*26	24.0	*27	47.0	*26	5.0	*35	55.0	*19	32.9	29
	1.3b	29.9 (26.2)	45	6.0	*48	19.0	*35	27.0	49	0.0	51	40.0	40	20.3	45
DeepSeeker-1.5-Inst	7b	68.9 (63.4)	*15	37.0	*10	37.0	*13	66.0	*8	24.0	8	60.0	*12	48.8	10
DeepSeeker-1.5	7b	42.1 (34.8)	*35	21.0	*26	34.0	*17	43.0	*31	4.0	*37	54.0	*21	33.0	28
CodeLlama-Inst	70b	66.5 (59.8)	*18	31.0	16	41.0	*10	65.0	*10	18.0	*15	65.0	5	47.7	12
	34b	51.8 (43.9)	25	22.0	*24	27.0	23	43.0	*31	9.0	*28	47.0	*27	33.3	27
	13b	48.8 (42.7)	29	21.0	*26	25.0	*25	46.0	29	8.0	*31	54.0	*21	33.8	26
	7b	43.3 (39.0)	33	14.0	38	18.0	*37	40.0	*37	8.0	*31	44.0	*33	27.9	36
CodeLlama	70b	60.4 (52.4)	23	25.0	21	29.0	*20	49.0	*23	14.0	*21	63.0	*8	40.1	22
	34b	52.4 (43.3)	24	15.0	37	24.0	*27	47.0	*26	11.0	*25	44.0	*33	32.2	30
	13b	42.7 (36.6)	34	18.0	*32	24.0	*27	38.0	*39	6.0	34	48.0	*25	29.4	33
	7b	39.6 (36.6)	39	10.0	*42	15.0	41	42.0	34	3.0	*39	44.0	*33	25.6	38
WizardCoder	34b	61.6 (54.3)	22	24.0	22	32.0	19	55.0	20	17.0	*18	55.0	*19	40.8	20
WizardCoder-1.1	33b	73.8 (69.5)	10	48.0	4	48.0	4	66.0	*8	20.0	13	64.0	*6	53.3	5
XwinCoder	34b	68.9 (62.2)	*15	33.0	*13	42.0	*7	67.0	*5	15.0	20	60.0	*12	47.7	13
Phind-CodeLlama-2	34b	70.7 (66.5)	13	22.0	*24	35.0	16	63.0	15	25.0	*6	58.0	15	45.6	16
Code Millennial	34b	73.2 (69.5)	11	35.0	12	41.0	*10	65.0	*10	17.0	*18	56.0	18	47.9	11
Speechless-CL	34b	75.0 (69.5)	7	38.0	9	37.0	*13	64.0	*13	23.0	*9	59.0	14	49.3	9
Magicoder-s-DS	6.7b	76.8 (70.7)	*5	40.0	*6	34.0	*17	67.0	*5	21.0	*11	61.0	*10	50.0	8
Magicoder-s-CL	7b	70.1 (65.9)	14	27.0	19	26.0	24	58.0	19	11.0	*25	52.0	23	40.7	21
StarCoder2	15b	45.1 (36.0)	*31	16.0	*35	19.0	*35	41.0	*35	5.0	*35	48.0	*25	29.0	35
	7b	34.8 (31.1)	*40	12.0	*39	17.0	39	38.0	*39	2.0	*45	46.0	*29	25.0	40
	3b	31.1 (26.2)	44	8.0	*45	14.0	*42	31.0	*44	2.0	*45	35.0	45	20.2	46
StarCoder	15b	34.8 (30.5)	*40	12.0	*39	11.0	47	37.0	41	2.0	*45	44.0	*33	23.5	41
Mixtral-Inst	8x7b	42.1 (38.4)	*35	21.0	*26	18.0	*37	41.0	*35	9.0	*28	45.0	*31	29.3	34
Mistral-Inst-v02	7b	28.0 (23.2)	*48	8.0	*45	16.0	40	25.0	50	3.0	*39	8.0	51	14.7	50
Mistral-Inst	7b	28.7 (24.4)	47	6.0	*48	8.0	50	31.0	*44	3.0	*39	29.0	48	17.6	49
Mistral	7b	28.0 (23.8)	*48	8.0	*45	14.0	*42	30.0	47	3.0	*39	38.0	43	20.2	47
OpenChat	7b	71.3 (66.5)	12	33.0	*13	29.0	*20	62.0	16	14.0	*21	43.0	38	42.1	18
stable-code	3b	29.3 (25.6)	46	10.0	*42	10.0	*48	31.0	*44	3.0	*39	41.0	39	20.7	43
Gemma-Inst	7b	28.0 (23.2)	*48	6.0	*48	10.0	*48	29.0	48	2.0	*45	31.0	47	17.7	48
Gemma	7b	31.7 (25.0)	43	12.0	*39	13.0	*44	40.0	*37	2.0	*45	39.0	*41	23.0	42
	2b	22.0 (17.1)	51	2.0	51	6.0	51	24.0	51	2.0	*45	21.0	50	12.8	51
Phi-2	2.7b	50.0 (45.1)	*27	18.0	*32	23.0	*30	49.0	*23	14.0	*21	37.0	44	31.8	32
Qwen-1.5	72b	67.1 (61.6)	17	28.0	18	28.0	22	61.0	*17	21.0	*11	47.0	*27	42.0	19
	14b	50.0 (45.7)	*27	20.0	*30	23.0	*30	48.0	25	18.0	*15	44.0	*33	33.8	25
	7b	42.1 (37.8)	*35	16.0	*35	13.0	*44	43.0	*31	7.0	33	32.0	46	25.5	39
Qwen	14b	46.3 (43.9)	30	23.0	23	20.0	34	45.0	30	13.0	24	45.0	*31	32.1	31
	7b	34.1 (29.9)	42	9.0	44	12.0	46	36.0	*42	4.0	*37	28.0	49	20.5	44

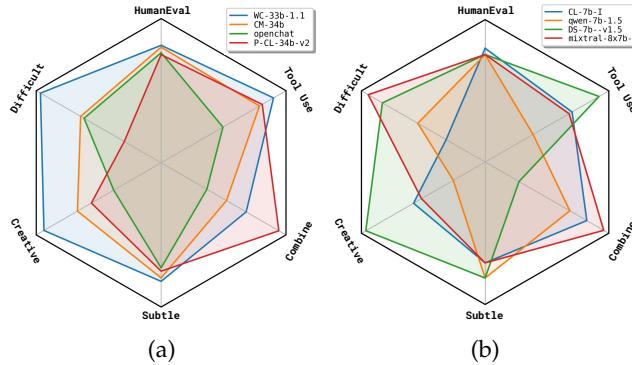


Figure 6: Radar graph of selected models with similar HUMANEVAL scores.

(DIFFICULT: 58.7%, CREATIVE: 50.2%, SUBTLE: 5.0%, COMBINE: 78.1%, and TOOL_USE: 4.9%). Additionally, this drop is not uniform across all LLMs and can range from 19.6% to 47.7%.

LLMs struggles on EVOEVAL benchmarks compare to high performance achieved on HUMANEVAL. One surprising finding is that, on SUBTLE, where only small changes are made to original problem with the roughly the same level of difficulty, the average performance of LLMs drops by 24.0% across the same 100 problems. It is important to note that, as the pass@1 score is generally higher on the first 100 problems than the complete 164 HUMANEVAL problems, this back-to-back performance drop is much higher than the performance drop from HUMANEVAL to SUBTLE mentioned above (which is 5.0%). Furthermore, we can also identify LLMs which struggle heavily on specific types of problems compared to their relative performance on HUMANEVAL. Figure 4 shows scatter plot of HUMANEVAL+ and EVOEVAL scores of selected LLMs. As we saw before, the significant portions of the models tends to be worse on EVOEVAL than HUMANEVAL (i.e., purple shaded region). However, there exists LLMs that have a *much* higher HUMANEVAL score compared to their performance on EVOEVAL (i.e., blue shaded region). This highlights potential data leakage of popular benchmarks where LLM performances are artificially inflated but do not translate to more difficult or other program synthesis problems.

Significant ranking changes of LLMs across different EVOEVAL benchmarks. In Figure 5, compared to the existing parity – where top models all perform similarly on HUMANEVAL, we observe drastic differences in ranking changes on EVOEVAL. We observe that while the relative difference between the top 5 models on HUMANEVAL is less than 10%, the difference on EVOEVAL on average is over 20%. Due to such saturation in top model performance, existing benchmarks may not reliably rank the program synthesis ability of each model. Taking a closer look at specific models, while Claude-3 and GPT-4 are tied for the 2nd best HUMANEVAL score, they both excel at different types of problems: GPT-4 performs best on difficult and creative problems while Claude-3 can better reason about helper functions in TOOL_USE and are less affected by subtle changes from original HUMANEVAL. Furthermore, while GPT-4-Turbo achieves the top HUMANEVAL and HUMANEVAL+ score, it falls off compare to the base GPT-4 variant where it is worse on DIFFICULT, CREATIVE and COMBINE problems. Such evaluation cannot be gained through naively reporting existing coding benchmark performance. Overall, by evolving the original benchmark into more difficult and diverse problems of different types, EVOEVAL can provide a more holistic evaluation and ranking of the coding ability of LLMs.

EVOEVAL can be used to comprehensively compare multiple models. Figure 6 shows two radar graphs of two sets of LLMs. In Figure 6a, while both WizardCoder-1.1 and Phind-CodeLlama-2 are top performing LLMs and have similar HUMANEVAL scores, they perform drastically differently across the benchmarks in EVOEVAL. WizardCoder-1.1 is better on DIFFICULT and CREATIVE and Phind-CodeLlama-2 are better on COMBINE problems. This can be partially explained through the training dataset used in each LLM where WizardCoder-1.1 uses an evolving dataset to generate more complex and difficult problems

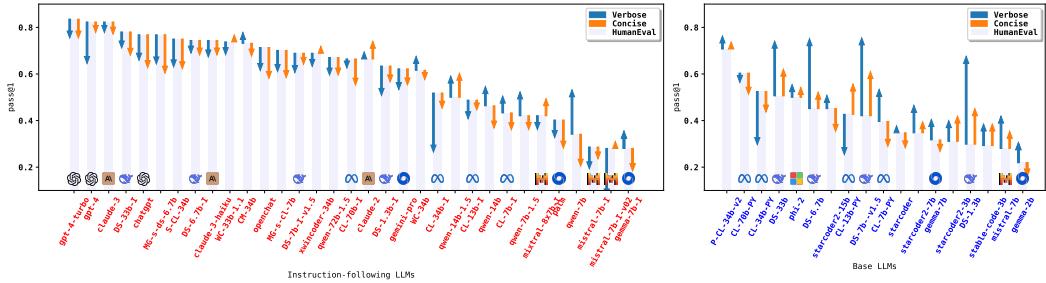


Figure 7: HUMAN-EVAL pass@1 separated into instruction-following and non-instruction-following LLMs with relative decrease or increase in pass@1 on VERBOSE and COMBINE.

whereas Phind-CodeLlama-2 is fine-tuned on high quality programming problems that seems to boost the ability to solve programs which combines multiple smaller programming concepts. Similar phenomenon can also be observed in Figure 6b. Different from just reporting a singular pass@ k score, EVOEVAL also allows detailed analysis across the different dimension of coding capability to identify particular domains or type of synthesis questions the LLM struggles or excels in.

Instruction-following LLMs are sensitive to subtle or rephrasing of problem docstring. Unlike the semantic-altering benchmarks in EVOEVAL, the semantic-preserving problems do not always lead to a decrease in performance. Figure 7 shows the HUMAN-EVAL score (bar) and the relative performance drop or improvement (arrows) on VERBOSE and CONCISE separated into instruction-following and base LLMs. We observe that almost all instruction-following LLMs drops in performance (on average 3.4% and 4.0% decrease on VERBOSE and CONCISE respectively) when evaluated on the two semantic-preserving dataset compared to the original HUMAN-EVAL. This is drastically different from the non-instruction-following variants where we even observe performance improvements (on average 0.5% and 2.1% increase on VERBOSE and CONCISE respectively). VERBOSE and CONCISE do not change the semantic meaning of the original problem except reword it in either a more verbose or concise manner. Prior work [11] has shown that by smartly rephrasing the original problem description, one can further boost LLM performance and we observe the similar phenomenon here mostly only for non-instruction-following models. This further points to possibility of overfitting to the exact descriptions utilized in HUMAN-EVAL especially for instruction-tuned LLMs.

Additionally, even on the semantic-altering benchmark of SUBTLE, where only subtle changes to the original problem are applied, on average, instruction-following LLMs drops by 7.6% whereas base models only decreases by less than 1% relative to their HUMAN-EVAL performance. These findings across LLM types show that while instruction-tuning is expected to align better with detailed task instructions, it fails to distinguish between these subtle changes in docstring, indicating potential memorization or contamination of prior evaluation benchmarks.

5.2 Problem Composition

Composition problems. The ability to compose different known concepts to solve new problems is known as *compositional generalization* [24]. This skill is essential for code synthesis, especially for complex problems in real-world programs. However, measuring compositional generalization in LLM presents a fundamental challenge since it requires controlling the relationship between training and test distributions [41]. While it is not easy to control the pre-training data of LLMs, we have more control in the testing phase. Hence, we focus on program concepts that have been demonstrated to fall within the capabilities of an LLM, and explore whether this proficiency extends to the combination of program concepts. As such, we start by taking a deeper look at the COMBINE problems evolved from combining previous HUMAN-EVAL problems.

Table 3: Detailed results of top performing LLMs on COMBINE and COMBINE-NAIVE. “HUMAN EVAL” is categorized into “pass both”, “pass one” and “pass none”, depending on the success on the two parent problems used to create COMBINE and COMBINE-NAIVE. “COMBINE (Solved)” and “COMBINE-NAIVE (Solved)” then show the distribution of successfully solved problems in the composition dataset that came from the previous categories. “Composition Percentage” is defined as the percentage of “pass both” problems the LLM can still solve when combining both of these problems.

	Size	HUMAN EVAL			COMBINE (Solved)			Composition Percentage
		pass both	pass one	pass none	pass both	pass one	pass none	
◎ GPT-4 ²⁰	NA	93	7	0	50	3	0	53.8%
◎ GPT-4-Turbo ²⁰	NA	79	19	2	38	6	1	48.1%
▲ Claude-3 ²⁰	NA	81	19	0	35	7	0	43.2%
◎ ChatGPT ²⁰	NA	65	34	1	24	9	0	36.9%
❖ DeepSeeker-Inst ²⁰	33b	71	27	2	29	2	0	40.8%
▲ Claude-3-haiku ²⁰	NA	63	34	3	19	6	0	30.2%
❖ DeepSeeker-1.5-Inst ²⁰	7b	62	37	1	18	6	0	29.0%
● Gemini ²⁰	NA	46	45	9	19	2	2	41.3%

	HUMAN EVAL			COMBINE-NAIVE (Solved)				
◎ GPT-4 ²⁰	NA	1018	55	1	766	7	0	75.2%
◎ GPT-4-Turbo ²⁰	NA	863	195	16	407	61	3	47.2%
▲ Claude-3 ²⁰	NA	796	268	10	359	96	1	45.1%
◎ ChatGPT ²⁰	NA	799	261	14	474	79	1	59.3%
❖ DeepSeeker-Inst ²⁰	33b	740	304	30	462	95	5	62.4%
▲ Claude-3-haiku ²⁰	NA	592	409	73	286	133	17	48.3%
❖ DeepSeeker-1.5-Inst ²⁰	7b	634	372	68	393	130	17	62.0%
● Gemini ²⁰	NA	364	535	175	225	205	37	61.8%

First half of Table 3 shows the detailed breakdown of the COMBINE dataset results on the top 8 performing LLMs. We observe that almost all problems solved in COMBINE came from the pass both category, which is intuitive as we do not expect LLMs to solve a problem composed of subproblems that it cannot already solve. However, we see that overall, the composition percentage is quite low as only GPT-4 is able achieve greater than half. This demonstrates, for the first time, that while state-of-the-art LLMs can achieve a high pass rate on simple programming tasks in general-purpose languages like Python, they still struggle with generalizing and composing these known concepts to address more complex problems.

Naive combination problems. Since COMBINE problems are not guaranteed to not contain additional new logic or concepts, we build a simplified dataset for sequential composition. Let A and B be two separate problems with x as input(s) for A , we aim to create a new problem C with same inputs where the solution can be written as $B(A(x))$. To accomplish this, the new problem includes a sequential docstring by attaching the docstring of problem A followed by B . Directly concatenating them will lead to unclear descriptions, as such, for each problem in HUMAN EVAL, we manually create two separate variants based on which order the problem may come in the new docstring. Figure 8 shows an example naive combination problem with the manual sequential instruction highlighted in red. Using these modified problem docstrings, we build a sequential combination dataset – COMBINE-NAIVE, containing 1074 problems by randomly combining problems filtering for input output matching (i.e., type of $A(x)$ should equal to type of y in $B(y)$).

The latter half of Table 3 shows the results on COMBINE-NAIVE following the same setup as COMBINE. We observe that while the composition percentage on the naive dataset improves significantly compared to the evolved COMBINE dataset, it still fails to reach near perfection, with the best LLM being able to only solve 3/4 of prior pass both problems. While existing

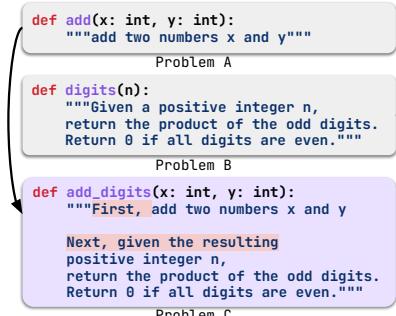


Figure 8: COMBINE-NAIVE problem

Table 4: Detailed results of top performing LLMs on DECOMPOSE. “HUMAN EVAL” shows the pass/fail breakdown of the 50 seed HUMAN EVAL problems. Each of these 50 problems, initially pass or failed, is decomposed into two subproblems. These are further categorized into “pass both”, “pass one” and “pass none”, based on whether the LLM can solve both subproblems. “Decomp. %” is the percentage of originally passing problems for which the LLM can solve both decomposed subproblems. Similarly, “Recomp. %” is the percentage of originally failing problems for which the LLM can solve both decomposed subproblems.

Size	HUMAN EVAL	DECOMPOSE						Decomp. %	Recomp. %	
		HUMAN EVAL pass			HUMAN EVAL fail					
		pass	fail	both pass	one pass	both fail	both pass	one pass	both fail	
GPT-4 ²⁰	NA	47	3	37	10	0	0	3	0	78.7%
GPT-4-Turbo ²⁰	NA	39	11	29	9	1	4	6	1	74.4%
Claude-3 ²⁰	NA	39	11	26	11	2	6	5	0	66.7%
ChatGPT ²⁰	NA	33	17	19	13	1	11	4	2	57.6%
DeepSeeker-Inst ²⁰	33b	33	17	18	14	1	8	9	0	54.5%
Claude-3-haiku ²⁰	NA	28	22	16	10	2	11	11	0	57.1%
DeepSeeker-1.5-Inst ²⁰	7b	27	23	18	8	1	9	11	3	66.7%
Gemini ²⁰	NA	19	31	13	6	0	10	18	3	68.4%
										32.3%

training or inference paradigms for LLMs for code focus on obtaining high quality datasets boosted with instruction-tuning, our result shows that existing LLMs still struggle with the concept of problem composition to tackle more complex problems. We hope future research can design novel training methods to tackle this limitation.

5.3 Problem Decomposition

Given our analysis and benchmark on combining different problems together, a nature follow-up would be to look at *problem decomposition* – decomposing larger problems into multiple subproblems. We start by selecting 50 HUMAN EVAL problems and then follow our approach in Section 2 to decompose each original problem into two smaller subproblems, creating 100 problems in our DECOMPOSE benchmark.

Table 4 shows the results of selected LLMs on DECOMPOSE (the same set of LLMs as COMBINE). We first observe that similar to the composition percentage in the COMBINE and COMBINE-NAIVE problems, LLMs do not achieve a high decomposition percentage. One possible interpretation is that current LLMs are trained to memorize or recover seen outputs in their training data, and when used for program synthesis, they cannot generalize the concepts from training data. This is demonstrated by not being able to solve smaller subproblems obtained from solved more difficult parent problems. On the other hand, we show that LLMs can sometimes solve both smaller subproblems even when the original parent problem is not solved (i.e., recombination percentage). DECOMPOSE is akin to breaking the harder problem down into easier subproblems, which is related to planning in prior work [22]. We hope future work can again build on these insights to achieve the best of both worlds in being able to successfully generalize difficult concepts into subproblems and adopting decomposing/planning to solve additional challenging problems.

5.4 Tool Using

We further analyze the TOOL_USE dataset, which contains pre-defined helper or auxiliary functions in addition to the main synthesis problem. Additionally, we construct TOOL_USE-MAIN_ONLY dataset, which contains the same set of problem as TOOL_USE, except that the input to the LLM consists only of the main problem description without including any helpers. Using both datasets together, we can evaluate the ability of LLMs to use helper functions to solve more complex problem. We observe that compared to scenarios without any helper functions (average pass@1 of 28.6%), LLMs on average improve by 81.3% when provided with the helper functions. This is to be expected as the helper functions provides additional utilities in aiding to solve the more complex problem. However, this improvement is not uniform, as we see that the average improvement when given the auxiliary functions

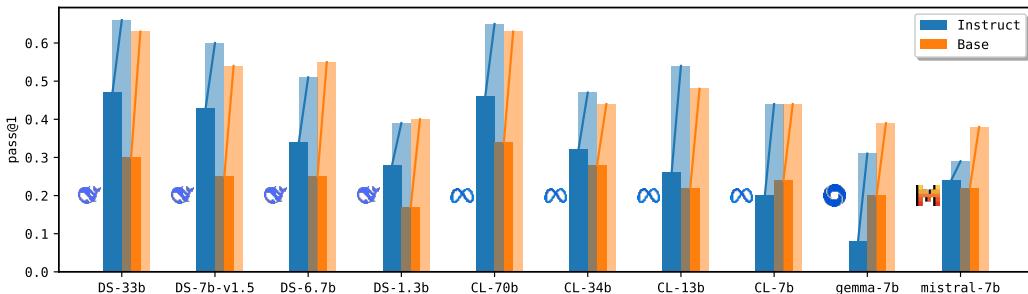


Figure 9: pass@1 improvement from TOOL_USE-MAIN_ONLY to TOOL_USE on selected instruction-following models and their base variants.

for instruction-following models is only 60.4% compared to the non-instruction-following LLMs’ improvement of 122.0%.

Figure 9 show the detailed comparison between 10 instruction-following and their base LLMs on both the TOOL_USE-MAIN_ONLY and TOOL_USE dataset. We observe that without the helpers, the instruction-following models significantly outperform their base LLMs. However, once the helpers are provided, this gap is drastically decreased, with cases even where the base models outperform their instruction-following counterparts. As real-world coding involves understanding, using, and then reusing existing functions across different places in the repository, being able to successfully leverage auxiliary methods is key. Current instruction-following LLMs are generally fine-tuned with data consisting of self-contained code snippets without the interaction and learning of function usages. This is further exacerbated by prior benchmarks, which mostly use self-contained functions, thus cannot expose the insufficient tool-using capability of such models. In EVOEVAL, with TOOL_USE and TOOL_USE-MAIN_ONLY, we demonstrate this gap in evaluation and hope to inspire future research on this important aspect of code LLMs.

6 Related Work

Large language models for code. Starting with the general development of LLMs for general purpose tasks, developers have applied LLMs to perform code-related tasks by further training LLMs using collected code snippets from open-source repositories. Such LLMs include CODEX [10], PolyCoder [52], CodeT5 [48], CodeGen [34], InCoder [14], CodeLlama [40], StarCoder [26], StarCoder2 [29], DeepSeeker [16], etc. These LLMs can autoregressive complete code given the relevant prefix (e.g., docstrings for function completion). More recently, following the advancement in NLP, researchers have applied instruction-tuning methods to train code-specific LLMs that are well-versed in following instructions. Examples of such LLMs include CodeLlama-Inst [40] and DeepSeeker-Inst [16]. WizardCoder [30] instruction-tunes the model using Evol-Instruct to create more complex instructions. Magicoder [50] develops OSS-Instruct by synthesizing high quality instruction data from open-source code snippets. OpenCodeInterpreter [55] additionally leverages execution feedback for instruction-tuning in order to better support multi-turn code generation and refinement.

Program synthesis benchmarking. HUMAN EVAL [10] and MBPP [4] are two of the most widely-used handcrafted code generation benchmarks complete with test cases to check for the correctness of LLM outputs. Building on these popular benchmarks, additional variants have been crafted including: HUMAN EVAL+ [28] which improves the two benchmarks with more complete testcases; HUMAN EVAL-X [54] which extends HUMAN EVAL to C++, Javascript and Go; MultiPL-E [9] which further extends both HUMAN EVAL and MBPP to 18 coding languages. Similarly, other benchmarks have been developed for specific domains: DS-1000 [25] and Arcade [53] for data science APIs; ODEX [49] for open-domain code generation covering a diverse range of libraries; CodeContests [27], APPS [17] and LiveCodeBench [20] for programming contests; ClassEval [13] for class-level generations, and

SWE-Bench [23] for real-world software engineering tasks. Different from prior benchmarks which require handcraft problems from scratch – high manual effort or scrape open-source repositories or coding contest websites – leading to unavoidable data leakage, EVOEVAL directly uses LLMs to *evolve* existing benchmark problems to create new complex evaluation problems. Furthermore, contrasting with the narrow scope of prior benchmarks (often focusing on a single type or problem, i.e., coding contests), EVOEVAL utilizes targeted transformation to evolve problems into different domains, allowing for a more holistic evaluation of program synthesis using LLMs.

7 Conclusion

We present EVOEVAL – a set of program synthesis benchmarks created by *evolving* existing problems into different target domains. We build on top of the popular HUMANEVAL benchmark to produce 828 problems across 7 different benchmarks for a holistic and comprehensive evaluation of LLM program synthesis ability. Our results on 51 LLMs show that compare to high performance on standard benchmarks, there is drastic drop in performance (on average 39.4%) when evaluated on EVOEVAL. Additionally, we observe significant ranking differences compared to previous leaderboards, indicating potential overfitting of popular LLMs on existing benchmarks. Throughout the paper, we provide additional insights, including the brittleness of instruction-following LLMs as well as problem composition and decomposition abilities. We hope EVOEVAL not only provides a valuable benchmarking suite for program synthesis but also inspires future code LLM builders to recognize the shown limitations of existing code LLMs and develop novel and targeted training approaches for code. We have open-sourced the EVOEVAL benchmarks, tools, and complete LLM generations available at <https://github.com/evo-eval/evoeval>

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A Evaluation LLMs

A.1 Evaluated LLMs

Table 5 shows the overview of the 51 LLMs we evaluated in our work. For any LLMs which provide their open-source weights, we directly obtain them from huggingface model hub [19]³. For any close-sourced LLMs, we directly access their model endpoints using their providers. For more detail on the access of each LLM, please check our repository: <https://github.com/evo-eval/evoeval>

A.2 Detailed Evaluation Setup

```
Please complete the following code snippet.
def transform_canvas(canvas: str) -> str:
    """
    You have an canvas containing either '#' (representing a wall), '-' (
    ↪ representing
    an empty space), or 'P' (representing the point at which a painter starts).
    ↪ The painter
    can move horizontally on the canvas and paints all empty spaces he encounters
    with '*' without crossing or hitting the walls.

    The task is to return an updated canvas with all the accessible spaces
    ↪ painted,
    keeping wall configuration and unaccessible spaces same. If the canvas
    ↪ contains no painter 'P',
    return the canvas as it is. If there are more than one 'P' or the number of
    ↪ painted space divides the empty spaces evenly, return 'Invalid canvas'.

    Examples:

    >>> transform_canvas('P----#----#----#----')
    'P****#----#----#----'

    >>> transform_canvas('--#-P#----#----#--#--')
    'Invalid canvas'

    >>> transform_canvas('-----#--P--#----#----')
    '-----##*P**#----#----'

    >>> transform_canvas('-----#----#--P---#P----')
    'Invalid canvas'
    """
```

Figure 10: Example input prompt for GPT-4

LLM generation. As mentioned in Section 4, we report the pass@1 score for each LLM on our dataset generated using greedy decoding (i.e., sampling with temperature = 0). For each LLM, we provide a specific input prompt depending on the model type. For base LLMs (i.e., not instruction-following variants), we use only the function headers as input. For instruction-following, we make the best effort to follow examples provided by each model maker on the exact instruction and format to use at the time of writing. Specifically, for instruction-following LLMs, we ask the model to return the code snippet wrapped by code blocks (i.e., ```). Figure 10 shows an example input for GPT-4 on a CREATIVE problem.

Furthermore, we also provide a custom sanitization script adopted from EVALPLUS [28] which parses the raw LLM outputs for code block parsing (e.g., removing `` indicators for

³For certain LLMs, we may use the vLLM inference library for more efficient generation

Table 5: Detailed overview of evaluated models. Model ID indicates either the API endpoint name or huggingface model name used for the particular model. Available Weights indicate whether the model is evaluated by accessing a close-sourced API endpoint or ran locally with provided weights. Note: 🤗 denotes instruction-following LLMs

	Size	Model ID	Available Weights
⌚ GPT-4-Turbo [36]	NA	gpt-4-0125-preview	✗
⌚ GPT-4 [36]	NA	gpt-4-0613	✗
⌚ ChatGPT [35]	NA	gpt-3.5-turbo-0125	✗
🅰️ Claude-3 [3]	NA	claude-3-opus-20240229	✗
🅰️ Claude-3-haiku [3]	NA	claude-3-haiku-20240307	✗
🅰️ Claude-2 [2]	NA	claude-2.1	✗
🌐 Gemini [43]	NA	gemini-1.0-pro	✗
🌐 PaLM-2 [1]	NA	text-bison-001	✗
⌚ DeepSeeker-Inst [16]	33b 6.7b 1.3b	deepseek-ai/deepseek-coder-33b-instruct deepseek-ai/deepseek-coder-6.7b-instruct deepseek-ai/deepseek-coder-1.3b-instruct	✓ ✓ ✓
⌚ DeepSeeker [16]	33b 6.7b 1.3b	deepseek-ai/deepseek-coder-33b-base deepseek-ai/deepseek-coder-6.7b-base deepseek-ai/deepseek-coder-1.3b-base	✓ ✓ ✓
⌚ DeepSeeker-1.5-Inst [16]	7b	deepseek-ai/deepseek-coder-7b-instruct-v1.5	✓
⌚ DeepSeeker-1.5 [16]	7b	deepseek-ai/deepseek-coder-7b-base-v1.5	✓
♾️ CodeLlama-Inst [40]	70b 34b 13b 7b	codellama/CodeLlama-70b-Instruct-hf codellama/CodeLlama-34b-Instruct-hf codellama/CodeLlama-13b-Instruct-hf codellama/CodeLlama-7b-Instruct-hf	✓ ✓ ✓ ✓
♾️ CodeLlama [40]	70b 34b 13b 7b	codellama/CodeLlama-70b-Python-hf codellama/CodeLlama-34b-Python-hf codellama/CodeLlama-13b-Python-hf codellama/CodeLlama-7b-Python-hf	✓ ✓ ✓ ✓
WizardCoder [30]	34b	WizardLM/WizardCoder-Python-34B-V1.0	✓
WizardCoder-1.1 [30]	33b	WizardLM/WizardCoder-33B-V1.1	✓
XwinCoder [45]	34b	Xwin-LM/XwinCoder-34B	✓
Phind-CodeLlama-2 [37]	34b	Phind/Phind-CodeLlama-34B-v2	✓
Code Millenials [8]	34b	budcosystem/code-millenials-34b	✓
Speechless-CL [42]	34b	uukuguy/speechless-codellama-34b-v2.0	✓
Magicoder-s-DS [50]	6.7b	ise-uiuc/Magicoder-S-DS-6.7B	✓
Magicoder-s-CL [50]	7b	ise-uiuc/Magicoder-S-CL-7B	✓
StarCoder2 [29]	15b 7b 3b	bigcode/starcoder2-15b bigcode/starcoder2-7b bigcode/starcoder2-3b	✓ ✓ ✓
StarCoder [26]	15b	bigcode/starcoder	✓
Ⓜ️ Mixtral-Inst [33]	8x7b	mistralai/Mixtral-8x7B-Instruct-v0.1	✓
Ⓜ️ Mistral-Inst-v02 [21]	7b	mistralai/Mistral-7B-Instruct-v0.2	✓
Ⓜ️ Mistral-Inst [21]	7b	mistralai/Mistral-7B-Instruct-v0.1	✓
Ⓜ️ Mistral [21]	7b	mistralai/Mistral-7B-v0.1	✓
OpenChat [46]	7b	openchat/openchat-3.5-0106	✓
stable-code [38]	3b	stabilityai/stable-code-3b	✓
🌐 Gemma-Inst [44]	7b	google/gemma-7b-it	✓
🌐 Gemma [44]	7b 2b	google/gemma-7b google/gemma-2b	✓ ✓
Phi-2 [32]	2.7b	microsoft/phi-2	✓
Qwen-1.5 [6]	72b 14b 7b	Qwen/Qwen1.5-72B-Chat Qwen/Qwen1.5-14B-Chat Qwen/Qwen1.5-7B-Chat	✓ ✓ ✓
Qwen [5]	14b 7b	Qwen/Qwen-14B-Chat Qwen/Qwen-7B-Chat	✓ ✓

instruction-following models) and end-of-string identifiers (e.g., removing tokens like `</s>`). Each model generated output is passed into the sanitization script and the evaluation occurs on the sanitized outputs.

Oracle. To evaluate the functional correctness of each LLM synthesized solution, we use differential testing by comparing the model output with the groundtruth output on a set of testcase inputs. We build our evaluation framework on top of the EVALPLUS evaluation script used for HUMANEVAL and HUMANEVAL+ benchmark which evaluates multiple problems and solutions in parallel for efficiency. For each testcase, we perform exact matching or check if the output is within an absolute difference threshold of 10^{-6} if the output is a floating point type. We additionally implement our evaluation script by recursively checking the type and performing the appropriate comparison (e.g., dictionary outputs are first length checked for equivalence and then matching is done for each value and key). Furthermore, we also implement custom oracles for specific problems where there could be multiple solutions or simple tolerance or exact matching cannot fully guarantee correctness. We refer the reader again to our repository <https://github.com/evo-eval/evoeval> which contains the full implementation of each of our custom oracle. Additionally, we also use timeout as another evaluation method. Our setting again follows EVALPLUS default setup where the timeout per problem is defined as $T = \max(T_{max}, f \times t_{gt})$ with default values of $T_{max} = 1000ms$, $f = 4$ and t_{gt} defined as the measured groundtruth solution time to produce the correct output. All timeout related factors can be adjusted to account for variance on different underlying machine and hardware.

B Transformation Prompts

```
Here is an example coding problem:  
{problem}  
  
Please increase the difficulty of the given coding problem  
  
You can increase the difficulty using the following method:  
- Add new constraints and requirements to the original problem, adding  
    ↪ approximately 10 additional words.  
- Replace a commonly used requirement in the programming task with a less common  
    ↪ and more specific one.  
- Add more reasoning steps.  
  
Return the new problem in the same format as the example problem (i.e.,
```

Figure 11: Prompt for DIFFICULT

```
Here is an example coding problem:  
{problem}  
  
Please generate a more creative coding problem.  
You should avoid common programming concepts and instead focus on creating a  
    ↪ problem that is interesting and fun to solve.  
Return the new problem in the same format as the example problem (i.e.,
```

Figure 12: Prompt for CREATIVE

Here we provide the exact targeted transformation prompts used to evolve existing benchmark problems into each of our transformation prompts. Figure 11, 12, 13, 14, 15, 16, 17 and 18 shows the prompt for DIFFICULT, CREATIVE, SUBTLE, COMBINE, TOOL_USE, VERBOSE, CONCISE and DECOMPOSE respectively.

Please add a subtle and simple change to the given problem.

You can change the problem using, but not limited to, the following methods:

Add one new requirement to the original problem, such as "Return the list in
 ↪ ascending order", "Return the list in ascending alphabetical order" and "
 ↪ Return unique elements only".

Invert one requirement of the original problem; for instance, reverse the
 ↪ instruction "from shortest to longest" to "from longest to shortest",
 ↪ reverse "maximum" to "minimum", or reverse "the first" to "the last".

Replace one requirement with another similar but different one; for example, if
 ↪ the original problem requires the values to be sorted, change it to
 ↪ keeping the original order.

Replace constants; for instance, replace zero with one.

Please only apply a minor change, ensuring that the new problem remains logical.
 ↪ Return the new problem in the same format as the original problem (Below
 is the question:problem

Figure 13: Prompt for SUBTLE

Here are two example problems:

Example problem 1:
 {problem_1}

Example problem 2:
 {problem_2}

Please create a new problem that combines problem 1 with problem 2 in a logical
 ↪ way. The new problem should seamlessly integrate the concepts from the
 ↪ two previous examples into a novel context, and require a solution that
 ↪ exercises the understanding of the concepts from both problems. It does
 ↪ not need to take all the inputs from both problems.

An incorrect way would be for the new problem to simply return the answers of the
 ↪ two problems separately. Another incorrect method would be to pass all
 ↪ inputs from both problems but some of them are not used to compute the
 ↪ output.

Return the new problem in the same format as the example problems in

Figure 14: Prompt for COMBINE

Figure 19 and 20 show the refinement and I/O extraction/fixing prompt used in EVOEVAL. The refinement prompt is used to refine the origin generated problem when inconsistency is detected (see Section 2). The extraction prompt is used to initially obtain a set of testcases from the problem docstring used for self-consistency evaluation. We further use an I/O fixing prompt (also in Figure 20) to fix any examples in the docstring which do not contain the right output (as computed by the groundtruth generated by GPT-4).

C Example Problems in EVOEVAL

Here we demonstrate a few example problems across the benchmarks in EVOEVAL and corresponding GPT-4 solution which cannot solve the problem. Figure 21, 22, 23, 24, 25,

Here is an example coding problem:
{problem}

Please come up with a new problem which uses helper functions to solve the
→ problem.

The new problem should contain the following:
first: one or more helper functions
second: the main problem description consist of the function header and docstring

The main problem description should not refer to the helper function(s) in any
→ way.

The helper function(s) should implement simple parsing or checking logic.

To solve the main problem, one should also use additional complex logic than just
→ calling the helper function(s).

Avoid problems on simple math concepts such as prime, palindrome, anagrams,
→ factorial

Avoid concepts like emails, string or parsing-based problems

Please return the full implementation of the helper function(s) and the main
→ problem description (not the implementation) in the same format as the
→ example problem (

Figure 15: Prompt for TOOL_USE

Below is a coding problem

{problem}

Make the docstring more verbose and detailed but preserve the semantic meaning
Ensure the function name, input argument names, and example input/output are the
→ same
Return the transformed problem in the same format as the original problem (i.e.,
→ function header + docstring)

Figure 16: Prompt for VERBOSE

Below is a coding problem

{problem}

Make the docstring shorter and more concise but preserve the semantic meaning
Ensure the function name, input argument names, and example input/output are the
→ same
Return the transformed problem in the same format as the original problem (i.e.,
→ function header + docstring)

Figure 17: Prompt for CONCISE

26 and 27 show such example for the EVOEVAL DIFFICULT, CREATIVE, SUBTLE, COMBINE, TOOL_USE, VERBOSE and CONCISE respectively.

Below is a complex coding problem
{problem}

Please decompose the above into 2 smaller sub problems
Return the two modified problems in the same format as the initial problem (i.e.,
 →

Figure 18: Prompt for DECOMPOSE

Below is a coding problem
{problem}

Ensure logical coherence in the given problem.
Improve the docstring's clarity and conciseness.
Fix missing or helpful imports.
Include example input/output if absent.
Return the modified problem in the same format as the example problem (i.e.,

Figure 19: Refinement prompt

Here is a function header with docstring:
{problem}

Please extract the example raw input argument and expected output from the
 → docstring.
If there are no example input and output please provide new ones.
Return each pair of input and output as assertions in this format:
assert {function_name}({{the_first_input_example}} == {{the_first_output_example
 → }}}
assert {function_name}({{the_second_input_example}} == {{
 → the_second_output_example}})
...

Here is a problem with docstring:
{problem}

Some example inputs and outputs in the docstring may be wrong. Please correct
 → them according to the provided correct assertions below, and ensure that
 → the correct example inputs and outputs assertionsReturn the revised
problem in the same format as the original problem (i.e.,

Figure 20: Input extraction and fixing prompts

```

def common(l1: list, l2: list, n: int):
    """
    Return the n longest strings, sorted by increasing length that are common in
    ↪ two lists.
    However, in the case of a tie, prioritize the string that appears first in
    ↪ list1.
    >>> common(["apple", "banana", "cherry", "date", "elderberry"], ["banana", " "
    ↪ date", "fig", "grape", "elderberry"], 3)
    ["banana", "date", "elderberry"]
    >>> common(["cat", "dog", "elephant", "fox", "goat"], ["dog", "fox", "cat", " "
    ↪ horse", "iguana", "goat"], 3)
    ["cat", "dog", "goat"]
    >>> common(["hello", "goodbye", "yes", "no", "maybe", "absolutely", "never"],
    ↪ ["no", "maybe", "absolutely", "always", "sometimes"], 1)
    ["absolutely"]
    """
    common_strings = [string for string in l1 if string in l2]
    common_strings.sort(key=len) # does not adjust for tie sorting scenario.
    return common_strings[-n:]

```

Figure 21: GPT-4 failing solution on problem EVOEVAL/58 in DIFFCULT

```

def crossword_validator(grid: list, words: list):
    """
    Consider a 2D grid representing a square crossword puzzle. Each cell of the
    → grid contains a single character.

    Determine if all the words from a provided list of words can be found in the
    → grid.
    Words can be found left-to-right (in a row), right-to-left (in a row),
    top-to-bottom down (in a column), and bottom-to-top (in a column).

    We assume that words are only found in contiguous cells and words do not '
    → wrap' around the grid.

    Note: the grid is a square (N x N) and all words are lowercase.

    Parameters:
    grid: list of list of char - where each char is a lowercase letter.
    words: list of str - where each str is a lowercase word.

    Returns:
    boolean - return True all words are found in the grid, False otherwise.

    >>> crossword_validator([['c', 'a', 't'], ['d', 'o', 'g'], ['d', 'o', 'p']],
    ↪ ['cat', 'dog', 'pop'])
    False
    >>> crossword_validator([['c', 'a', 't'], ['d', 'o', 'g'], ['d', 'o', 'p']],
    ↪ ['cdd', 'dog', 'pod'])
    True
    """

    n = len(grid)
    for word in words:
        found = False
        for i in range(n):
            # does not correctly check if a word can be found as a sublist of
            → column/grid
            if ''.join(grid[i]) == word or ''.join(grid[i][::-1]) == word:
                found = True
                break
            if ''.join([grid[j][i] for j in range(n)]) == word or ''.join([grid[j]
    ↪ ][i] for j in range(n)][::-1]) == word:
                found = True
                break
            if not found:
                return False
    return True

```

Figure 22: GPT-4 failing solution on problem EVOEVAL/21 in CREATIVE

```
from typing import List

def below_one(operations: List[int]) -> bool:
    """
    You're given a list of deposit and withdrawal operations on a bank account
    ↪ that starts with
    one balance. Your task is to detect if at any point the balance of account
    ↪ falls below one, and
    at that point function should return True. Otherwise it should return False.
    >>> below_one([1, 2, 3])
    False
    >>> below_one([1, 2, -4, 5])
    True
    """
    # incorrect starts balance at 0 instead of 1
    balance = 0
    for operation in operations:
        balance += operation
        if balance < 1:
            return True
    return False
```

Figure 23: GPT-4 failing solution on problem EVOEVAL/3 in SUBTLE

```

def grade_with_same_chars(grades: list, s0: str, s1: str):
    """
    A teacher has a special grading system where she assigns her students letter
    ↪ grades
    based on their GPA according to the following table:

        GPA      | Letter grade
        4.0      | A+
        > 3.7    | A
        > 3.3    | A-
        > 3.0    | B+
        > 2.7    | B
        > 2.3    | B-
        > 2.0    | C+
        > 1.7    | C
        > 1.3    | C-
        > 1.0    | D+
        > 0.7    | D
        > 0.0    | D-
        0.0      | E

    However, this year she adds an extra condition: the students can only receive
    ↪ a grade
    if their name (s0) and the course title (s1) have the same characters. The
    ↪ function
    receives a list of GPAs and two strings (s0 and s1) and returns a list of
    ↪ grades
    for the students that pass the condition, or an empty list if no student
    ↪ passes.

    Example:
    grade_with_same_chars([4.0, 3, 1.7, 2, 3.5], 'abcd', 'dcba') ==> ['A+', 'B',
    ↪ 'C-', 'C', 'A-']
    grade_with_same_chars([4.0, 3, 1.7, 2, 3.5], 'aaabcd', 'dddcba') ==> ['A+', ,
    ↪ B', 'C-', 'C', 'A-']
    grade_with_same_chars([4.0, 3, 1.7, 2, 3.5], 'abcd', 'dcbae') ==> []
    """
    # does not correctly check characters are same
    if sorted(s0) != sorted(s1):
        return []
    grading_system = {4.0: 'A+', 3.7: 'A', 3.3: 'A-', 3.0: 'B+', 2.7: 'B', 2.3: 'B-',
    ↪ 2.0: 'C+', 1.7: 'C', 1.3: 'C-', 1.0: 'D+', 0.7: 'D', 0.0: 'D-', 0.0: 'E'}
    grades_assigned = []
    for gpa in grades:
        for key in sorted(grading_system.keys(), reverse=True):
            if gpa >= key:
                grades_assigned.append(grading_system[key])
                break
    return grades_assigned

```

Figure 24: GPT-4 failing solution on problem EVOEVAL/28 in COMBINE

```

def is_valid_passport(passport: str) -> bool:
    """
    Checks whether a given string is a valid passport number.
    A valid passport number is defined as having exactly 9 alphanumeric
    ↪ characters.

    >>> is_valid_passport('P12345678')
    True
    >>> is_valid_passport('P123456789')
    False
    >>> is_valid_passport('P12345G78')
    False
    """

    if len(passport) != 9:
        return False
    if not passport.isalnum():
        return False
    return True

from typing import List, Tuple

def process_passport_data(data: str) -> List[Tuple[str, str]]:
    """
    Parse a string containing passport data and return a list of tuples.
    Each tuple contains the passport number and the name of the passport holder.
    The passport data string is in the format of 'PassportNumber:Name'
    separated by lines.

    Only process valid passport data. A valid passport number is defined as
    ↪ having exactly 9 alphanumeric characters.

    >>> process_passport_data('P12345678:John Doe\nX12345678:Jane Doe')
    [('P12345678', 'John Doe')]
    >>> process_passport_data('P12345678:John Doe\nA123456789:Jane Doe')
    [('P12345678', 'John Doe')]
    """

    valid_passports = []
    lines = data.split('\n')
    for line in lines:
        (passport, name) = line.split(':') # directly splits without checking for
        ↪ validity
        if is_valid_passport(passport):
            valid_passports.append((passport, name))
    return valid_passports

```

Figure 25: GPT-4 failing solution on problem EVOEVAL/23 in TOOL_USE

```

def starts_one_ends(n):
    """
    This function, given a user-provided positive integer 'n', calculates and
    ↪ returns the total count of n-digit positive integers where 1 appears
    ↪ either at the start or the end of the number.

    For instance, if the input is 2, the function will count all the two-digit
    ↪ numbers that either start or end with 1, like 10, 11, 21, 31, ..., 91,
    ↪ and 12, 13, ..., 19.

    It is important to note that this function only accepts positive integers. If
    ↪ a non-integer or non-positive integer is provided, the function may not
    ↪ behave as expected.

    Args:
    n : int
        A positive integer that represents the number of digits in the numbers to
    ↪ be counted.

    Returns:
    int
        The count of the numbers of n-digit positive integers that start or end
    ↪ with 1.

    Examples:
    The function can be called in the following way:
        starts_one_ends(2)
    This example call would return the count of two-digit numbers where 1 appears
    ↪ at the start or at the end.
    """
    if n == 1:
        return 1
    else:
        # incorrectly adds 2 to the final answer
        return 18 * 10 ** (n - 2) + 2

```

Figure 26: GPT-4 failing solution on problem HUMANEVAL/83 in VERBOSE

```

def circular_shift(x, shift):
    """Performs a circular right shift on the digits of x as per shift value and
    ↪ returns the result in string format.
    Returns reversed digits if shift exceeds number of digits.

    >>> circular_shift(12, 1)
    "21"
    >>> circular_shift(12, 2)
    "12"
    """
    x = str(x)
    # does not check shift exceeds string length and return reversed digits
    shift = shift % len(x)
    return x[-shift:] + x[:-shift]

```

Figure 27: GPT-4 failing solution on problem HUMANEVAL/65 in CONCISE